2015

# Attention and executive control during lexical processing in aphasia

BOSTON UNIVERSITY

SARGENT COLLEGE OF HEALTH AND REHABILITATION SCIENCES

Dissertation

# ATTENTION AND EXECUTIVE CONTROL DURING LEXICAL PROCESSING IN APHASIA

by


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Submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

2015

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## DEDICATION

I would like to dedicate this work to my patients and colleagues at Massachusetts General Hospital. Thank you for helping me find meaningful work, and for giving me reasons to keep asking difficult research questions.

## ACKNOWLEDGMENTS

While considering the scope and potential impact of this work, I am reminded of the large dirt piles I used to climb as a child while visiting work sites with my father; a relatively small feat by any general reckoning, but certainly a significant effort and accomplishment for me at the time.

Regardless of their size, most climbs require help and support, and I have many people to thank for this work. First, I would like to thank my research advisors, David Caplan and Gloria Waters for the thoughtful mentorship, numerous opportunities, and unconditional support they have offered me in the course of my training at Boston University. I cannot overstate the positive impact they have had on me as a scientist.

I would like to thank Randi Martin and Jeffrey Starns for all their advice, training, and feedback on this project, for their willingness to serve on my dissertation committee, and for their generosity in letting me spend time in their labs.

I would also like to thank the members of the Boston University Language Science Lab. Julie Bertram and Adam Ostrowski helped me with a great deal of problem solving, and I was lucky to have a number of wonderful research assistants to help with testing and research administration: sincere thanks to Jessie Connaughton, Danielle Fossa, Madeline Grimm, Caroline Malizia, Sarah Papan, Caitlin Roxby and Elisabeth Russell. I would also like to thank my funding sources for this work, the NIH-NIDCD and the Dudley Allen Sargent Research Fund.

I would like to thank my research participants for all their time, patience, and commitment to research, even in the face of potentially frustrating tasks and difficult transportation arrangements. I would also like to thank the members of the Boston University Aphasia Resource Center, the Boston University Aphasia Resource Laboratory, and colleagues at Massachusetts General Hospital, who all helped me a great deal with participant recruitment.

Finally, I would like to thank my friends and family for the large amount of love and support I received during this period of my life, and would like to specifically thank my father, Sanford Evans. Thank you for the company on all those walks to work, and for teaching me that I should never be afraid to think about problems fundamentally.

**ATTENTION AND EXECUTIVE CONTROL DURING**

**LEXICAL PROCESSING IN APHASIA**

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ABSTRACT

The goal of this project was to investigate the relationship between executive attention and specific linguistic and control processes during goal-directed tasks in aphasia. Its central premise was that PWA often possess dissociable impairments in linguistic processes and in the mechanisms that control and efficiently utilize those processes. The motivation for this claim was based on observations that PWA often present with deficits in the online processing of linguistic information, which in some instances have been interpreted as evidence for impaired linguistic operations, but in others has been interpreted as evidence for impaired *control* of language processing due to more general cognitive constraints. The current work tested claims regarding the Executive Attention model (Engle and Kane, 2004) in aphasia and its relation to varying task sets in linguistic and nonlinguistic tasks.

20 PWA and 23 matched controls were tested on four tasks measuring executive attention in verbal and nonverbal domains using word-picture interference, semantic and perceptual go/no-go, and spatial Stroop designs. Participants were also tested on lexical decision and numerosity judgment tasks with varying speed and accuracy-focused instructions, with performance modeled using the Diffusion Model (Ratcliff, 1978).

Overall, the current work found evidence for the predicted domain-general and domain-specific impairments in executive attention at the level of individual PWA. However, these executive attention deficits did not appear to be associated with difficulties adapting to shifting speed-accuracy constraints. In addition, group-level patterns of performance across experiments suggest an additional related executive control deficit in the area of generating and maintaining arbitrary stimulus-response mappings.

This study also demonstrated the appropriateness and potential applicability of the diffusion model in aphasia research, and diffusion model analyses found that PWA had difficulty adjusting their nondecision times in response to speed constraints, had lower drift rates in lexical decision, which reflected inefficient processing of lexical information, and had a disproportionately difficult time efficiently processing easy stimuli in lexical and numerosity tasks.

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# CHAPTER ONE.

## Introduction

The National Aphasia Association estimates that roughly 80,000 new individuals are diagnosed with aphasia as a result of stroke each year, and that there are currently ≈1 million people with aphasia (PWA) in the United States. Given its prevalence and the negative impact aphasia has on society, it is of great importance to improve our understanding of the cognitive-linguistic deficits associated with this disorder. The current dissertation seeks to address this by looking at the role of attention and cognitive control in lexical processing in PWA. Its central thesis is that PWA have impairments both in automatic linguistic processing and in the mechanisms that control and efficiently utilize those processes. Further, it is hypothesized that these dual impairments will be differentially sensitive to experimental manipulation, and will correlate with individual differences in aspects of attention and cognitive control in specific ways.

This project consists of six experiments conducted on a single set of PWA and matched controls. Experiments 1 through 4 investigate attention and executive function in PWA in linguistic and nonlinguistic domains, specifically by examining the construct of executive attention (Kane and Engle, 2003) and its relationship to controlled linguistic performance.

Experiments 5 and 6 characterize the ability of PWA to shift between speed and accuracy emphasis during a lexical decision and a nonlinguistic numerosity task, with results interpreted using a mathematical model of the decision process (the Diffusion model; Ratcliff, 1978). It is predicted that PWA and control's performance will differ on specific diffusion model parameters that will be related to how they process language and respond to different task constraints. It is also predicted that PWA will demonstrate worse performance than controls in the executive attention tasks, with a greater decrement in performance in linguistic compared to nonlinguistic measures, and that these differences will be predictive of PWA performance on the lexical decision tasks.

This dissertation is organized as follows: Chapters 2, 3, and 4 review literature relevant to the motivation and methods of the current work. Chapter 5 outlines the specific aims for the current project, while Chapter 6 outlines the general research design and methods for the current battery of experiments. Chapter 7 reports participant assessment and demographics. Chapters 8 through 11 report executive attention Experiments 1 through 4. Chapter 12 reports group comparisons between experiments 1 through 4, as well as patterns of association and dissociation at the individual level, and discusses general implications for the presence of executive attention impairments in aphasia. Chapters 13 and 14 report the lexical decision and numerosity tasks with varying speed and accuracy instructions, along with diffusion models of individual performance on these tasks. Chapter 15 reports comparisons between these experiments and measures of executive attention from Experiments 1 through 4. Chapter 16 concludes with the general discussion.

# CHAPTER 2

## Attention and Cognitive Control Accounts of Aphasia

### 2.1 Chapter Introduction

This chapter will outline theories that argue for a role of attention and cognitive control deficits in aphasia, contrasted against "traditional" theories that argue the disorder is better explained by selective impairments in specific linguistic operations or modules. It will then review selected literature documenting (a) the presence of general attention and executive deficits in PWA, and (b) evidence for semantic deficits in PWA that are specifically attributed to control deficits.

This discussion will be framed by issues regarding deficits in competence vs. performance, the relationship between resource allocation and modularity of function, and the relationship between controlled, goal-directed, and automatic processing. These sections will attempt to demonstrate the need for a new hybrid approach that acknowledges a potential role for both general control and linguistic processing impairments in aphasia.

This will be followed in Chapter 3 with a discussion of (a) a specific cognitive construct (i.e., executive attention) that will be useful in the current endeavor, and (b) the role of control in language processing as it relates to automaticity of function. Using these frameworks, the discussion will outline a hybrid aphasia model that makes specific predictions about the deficits that may occur due to the breakdown of one or more of these factors at the level of lexical processing.

### 2.2. Arguments for an Attention and Cognitive Control Account of Aphasia

Many authors have hypothesized that attention and executive control play a role in language processing (e.g., Ye & Zhou, 2009; Novick et al., 2005), and in language deficits experienced by PWA (e.g., Murray, 2002; Alexander, 2006). One well-cited example, which will be used to motivate the current hybrid theory, was proposed by McNeil et al. (1991), in which they claimed that aphasia is caused by general deficits in the allocation of attention during language processing. In motivating this theory, they laid out the history of what they claimed to be the dominant "paradigm of aphasia" (p. 21), and broke the development of this paradigm into three stages: they claimed that the first stage was characterized by the Wernicke-Lichtheim model of aphasia, in which damage to specific language centers and pathways resulted in specific aphasic syndromes. The second stage, beginning in the early 1970's and exemplified by the work of Harold Goodglass and colleagues, was directed towards mapping newly developed linguistic constructs onto the Wernicke-Lichtheim model. They stated that models during this stage tended to assume (implicitly or otherwise) that aphasic deficits were due to breakdowns in linguistic *competence* (the formal knowledge an individual possesses about a language), instead of linguistic *performance* (the actual implementation of that knowledge on-line; Chomsky, 1966). In this sense, these models of aphasia assumed a "loss" of the underlying knowledge of linguistic representations required to process linguistic content online. However, the third stage in the development of the aphasia paradigm was one in which aphasia was increasingly viewed as a performance-based "access" deficit (p. 23). McNeil et al. (1991) cited support from various sources for an online processing deficit view of aphasia (as opposed to a loss of knowledge/competence). This was expanded by Hula and McNeil (2008) into a number of lines of converging evidence, the most relevant of which are summarized below:

1. *Intact metalinguistic knowledge*. PWA "…often demonstrate metalinguistic knowledge about aspects of language that they fail to perform as they did premorbidly" (p. 171). They interpreted this as evidence that "fundamental properties of the language are intact, and factors required for their online construction and integration prevent their actualization" (p. 171).

2. *Priming.* PWA demonstrate priming effects at multiple linguistic levels (e.g., phonological- Milberg et al., 1988; associative- Prather et al., 1997; contextual- Martin et al., 2004; and syntactic- Haarmann & Kolk, 1991), implying that the relevant underlying representations must be intact at least to some degree, and that "…obligatory linguistic processing systems and operations are responsible for these effects" (p.171).

3. *Stimulability.* Since PWA improve linguistic performance in the presence of transcranial magnetic stimulation (Naeser et al., 2005), this also implies that underlying knowledge representations must still be present.

4. *Transience.* The fact that aphasic deficits frequently improve spontaneously over time (Lomas, & Kertesz, 1978) similarly suggests that underlying representations are not "lost" and then "relearned". Instead, "Either an interfering factor of some kind or a transient inaccessibility to the building blocks of the linguistic operation appear to account for the aphasia often seen in transient ischemic attack and reversible ischemic neurological disorder or in states of hypoperfusion" (p. 171).

5. *High variability.* One of the hallmarks of aphasia is the degree of variability in performance (Kolk, 2007). "This variability in performance occurs from month to month, week to week, day to day, hour to hour and even second to second. Further, the variable performance can occur on the same linguistic tasks under the same environmental and task-demand conditions" (Hula & McNeil, 2008, p. 172). They argue that since aphasic performance mirrors typical performance at times, underlying representations must be present.

When viewed as a whole, these lines of evidence rather convincingly argue for a processing-based conceptualization of aphasic deficits. However, the nature and exact locus of these online breakdowns is still very much a matter of debate. Many models that McNeil et al. (1991) placed within their third stage of aphasia paradigm development assumed a performance-based account of aphasia, but attributed the relevant breakdowns to impairments in specialized linguistic operations or "processing units" responsible for specific linguistic computations (e.g., Caplan and Hildebrandt, 1988). These processing units were assumed to be *modular* (Fodor, 1983), and as a result, susceptible to *selective impairment*. Models of this type obviate the need to place the locus of processing deficits in general attention or processing resources of any kind. However, McNeil et al. (1991) claimed that the overall support for models of this type were weak based on the following reasoning, with each of their points addressed in turn:

1. Subcomponents of language share resources, as evidenced by performance on dual tasks (e.g., phoneme monitoring and semantic judgment; Tseng at al., 1990). While this is evidence against modularity in its strictest sense, results of this type still leave room for significant encapsulation of linguistic function, provided there is some level or element of the two processes that possess a shared component or resource. For example, aspects of phonemic and semantic processing could be largely modular in the above example, with deficits in one task not necessarily entailing impairments in the other, but could both rely on the same control operations and ability to maintain stimulus-response mappings in the dual task.

2. PWA frequently have multi-modal and multi-domain deficits, and as a result, aphasia as a whole has often been defined as a multi-domain deficit. They claim that this argues against strict modularity-based accounts of aphasia, because "if linguistic computational operations (e.g., co-indexing pronouns) can be selectively impaired, one cannot define the language deficit (i.e., the aphasia) as being multi-domain" (McNeil et al., 1991, p. 26). However, this argument is flawed, as it presupposes that

the construct of aphasia must be holistic in nature, without subtypes being present within a unifying disorder.[1]

3. The strongest evidence for encapsulation-based models of aphasia comes from single and double dissociations. A single dissociation "occurs when a variable is found to selectively affect performance on one task but not on another" while a double dissociation "occurs when one variable affects performance only on the first task, while the other variable affects performance only on the second task." (Dunn & Kirsner, 1988, p. 91). In the context of aphasia, these dissociation are defined based on the presence of impairment on one linguistic task but not another, thereby implying functional independence of at least some of the linguistic operations involved in each. McNeil et al. (1991) state that intact vs. impaired performance is generally defined as either at/below chance performance on one measure and above chance on another when task probabilities can be determined, or when performance on one task is within range of normal performance, and performance on another is at/below chance. Although they cite very little literature, they claim that the evidence in support of dissociations based on these criteria is "weak" overall (McNeil et al., 1991, p. 26). Based on this conclusion, they state: "Either the actual computations are shared between linguistic domains or another mechanism common to the various linguistic computations is shared. Since there is little evidence that subcomponent processing units are modular, and in fact some rather compelling evidence that they

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[1] An example of a model/definition that would meet the requirements they specify while

> are not […], researchers are left with an option in which a superordinate mechanism is shared by linguistic processing units" (p. 28).

McNiel and colleagues go on to argue that this "superordinate mechanism" is in fact the deployment and control of attention during linguistic processing. However, just as they pointed out a number of issues with a "strong" modularity-based account of aphasia, there are clear problems with strong attention-based accounts as well. First, although many reported dissociations in the literature are weak when assessed in terms of the criteria outlined above, there are still some very strong cases of dissociation that support the idea of specialized domain-specific resources or operations, at least in some instances.

For example, Caramazza and Shelton (1998) presented an aphasia patient, E.W., who showed category-specific semantic deficits following a left CVA. Her performance for naming of non-animal pictures approached the typical range (94% compared to 99% control performance for high familiarity items; 81% compared to 99% control performance for low familiarity items), but was severely impaired for the naming of animal pictures (54% compared to 100% for high familiarity items; 28% compared to 95% for low familiarity items). This basic disparity in performance persisted even after controlling for category differences in familiarity, frequency, and visual picture complexity. Compared to her overall category naming performance for animals of 34%, she performed with 100% accuracy on many other categories, including the naming of clothing, fruit, furniture, and vegetables. There are also examples of double dissociation in this domain, with patients presenting with the opposite pattern of deficit (e.g., patient

"P.S." from Hillis and Caramazza, 1991). To account for patterns such as these, a theory of aphasia based strictly on attention allocation would have to be able to explain why allocation of general attentional resources alone could result in profound and consistent deficits in specific linguistic operations or domains. Given the evidence, it is more parsimonious to allow for the selective impairment of specific linguistic operations, at least in principle. Therefore, it is quite unlikely then that general attention/ control deficits can account for aphasia alone. Instead, a hybrid account acknowledging the potential role of both general cognitive and specialized linguistic impairments is called for. One such account will be outlined in a later section.

## 2.3. Literature Demonstrating the Presence of General Attention and Control Impairments in PWA

While a "strong" attention-based account of aphasia is untenable given the reasons listed above, there is nonetheless increasing evidence for the presence of attention and cognitive control deficits in PWA, a necessary (but insufficient) condition for attention-based accounts of aphasia in general. Some studies have focused simply on determining whether nonverbal impairments in attention or executive skills are present in PWA, while others have also looked at whether these abilities correlate with measures of language function. An example of the first type is a study by Erickson et al. (1996). The authors tested the nonlinguistic auditory sustained and divided attention abilities of 10 PWA (3–11 months post-onset of aphasia following left CVA) and 10 age-matched controls using a sustained attention task and a divided attention task. In the sustained attention task, subjects listened to 10 minutes of pure tones and complex harmonics and were asked to raise their hand every time they heard a complex harmonic (25% of trials). In the divided attention dual task, the tone monitoring task was the same, but subjects were also asked to sort cards according to color at a self-determined rate. They found that group performance did not differ in the simple sustained attention task, but that PWA were significantly less accurate at monitoring tones in the dual task, and concluded that "Aphasic individuals demonstrate an inability to properly allocate attentional resources to auditory signals, even nonspeech signals, in the presence of competing stimuli" (p. 250).

Murray (2012) looked at the attention, short-term/working memory, and executive function abilities of PWA and their relationship to language function. She tested a total of 39 PWA (at least 6 months post-onset of stroke) and 39 controls matched for age and IQ. Participants were given a battery of measures designed to assess cognitive and linguistic function. Attention measures included subtests of the Test of Everyday Attention (TEA; Robertson, Ward, Ridgeway, & Nimm-Smith, 1994), the Behavioral Inattention Test (BIT; Wilson, Cockburn, & Halligan, 1987), and the Rating Scale of Attentional Behavior (RSAB; Ponsford & Kinsella, 1991). Tests of short-term and working memory consisted of the forward and backward Visual Memory Span subtests of the Wechsler Memory Scale—Revised (Wechsler, 1987), and an auditory working memory protocol from Tompkins et al. (1994). Executive functions were assessed via the Ruff Figural Fluency Test (RUFF; Ruff, 1996). Language abilities were assessed via the Aphasia Diagnostic Profiles (Helm-Estabrooks, 1992). She found that PWA did significantly worse than controls on all attention tasks indicating that

> …each of the attention functions, modalities, and behaviors assessed in the current study (i.e., visual and auditory sustained and selective attention, visual and auditory attention switching, divided attention, visual neglect, presence and frequency of daily behaviors indicative of attention problems) are vulnerable in individuals with aphasia (Murray, 2012, p. S59).

PWA also performed significantly worse than controls on the working memory and executive control measures. In addition, she found a series of moderate-to-strong correlations between attention abilities as measured on TEA subtests and language ability as measured by subscores and overall severity score on the ADP, which she interpreted as evidence for a role of attention in PWA language performance. However, she also found that 5 PWA scored in the typical range on all subtests of the TEA and 3 PWA scored in the typical range on all attention measures, which she interpreted as evidence against the "strong attention" hypothesis outlined in the previous section.

In a large-scale study designed to norm the Aphasia Check List (ACL), an aphasia assessment for native speakers of German, Kalbe et al. (2005) tested 154 PWA (104 following an ischemic infarct), and 106 healthy unmatched controls. Part of their test was designed to assess cognition, with visual selective attention assessed via a timed symbol cancellation task, and nonverbal reasoning/ executive function assessed via matrix reasoning. They established norms using the control participants, with a cutoff of -1 standard deviations below the mean indicating impaired performance. Given these criteria, they found that a full 77% of PWA scored in the impaired range in the attention and 73% scored in the impaired range in the reasoning task. In addition, there were significant correlations between attention performance, auditory comprehension performance, and naming performance for PWA, but no significance correlations between these subtests for controls. However, these results would have been strengthened if impaired functioning had been defined more stringently (e.g., via the methods of Crawford and Howell, 1998), and controls had been matched to PWA participants for age and education.

Although the above studies have shown attention and executive impairments in tasks designed to minimize linguistic load, one often-raised concern is that impaired PWA performance on these tasks is in fact mediated by linguistic deficits (Murray, 2012). For example, linguistic deficits might negatively impact task comprehension or make the use of language-dependent strategies (e.g., covert verbal rehearsal of task goals) more difficult. Fucetola et al. (2009) sought to at least partially address this concern by looking at the relationship between verbal and nonverbal test performance using correlational and factor-analytic techniques. 136 English-speaking PWA (post unilateral left CVA; 91% ≤3 years post-stroke) were tested on the Boston Diagnostic Aphasia Examination (BDAE-3;), Boston Naming Test (BNT), and subtests from the Wechsler Adult Intelligence Scale (WAIS-III) and Wechsler Memory Scale (WMS-III), consisting of Block Design, Matrix Reasoning, Picture Arrangement, and Spatial Span. Previous work in healthy populations showed that performance on these nonverbal/ perceptual tests loaded well on a single latent factor (Tulsky and Price, 2003), and they found that a single-factor model of this type was also a good fit for PWA using confirmatory factor analysis. Although the presence of cognitive impairments in-and-of-themselves for PWA was not specifically addressed in this study, group scores for all WAIS and WMS subtests (with the exception of Matrix Reasoning) were > 1 SD below the population norm. They also used multiple regression techniques and found that "Overall, language competence, education, and years post stroke accounted for about 40% of the variance in nonverbal performance, with auditory comprehension (LCI-Auditory Comprehension component) accounting for 27% of the variance over and above the demographic characteristics of our sample." The authors concluded that "nonverbal cognitive performance is clearly related to aphasia severity, but not fully explained by it" (p. 1424).

## 2.4. The Need for Hybrid Cognitive-Linguistic Accounts of Aphasia

The previous sections established that, as a whole, aphasia is best described as a performance-based deficit instead of one based on the loss of linguistic competence. Evidence from a number of sources was also reviewed, demonstrating that there is good evidence for attention and executive function deficits in PWA, independent of language ability.

Despite arguments on both sides, there does not appear to be adequate support for either a "strong" version of the selective impairment or the attention-based account of aphasia. Therefore, since there is evidence for attention and control impairments in aphasia, and there is evidence for at least some selective impairments of specific linguistic processes, what is left is middle ground: the present claim is that while many linguistic operations are automatic, proceduralized, and effectively modular to some extent, their typical and efficient *implementation,* especially in explicitly goal-directed contexts, relies on the general recruitment of attention and cognitive control, and that deficits in any of these areas may contribute to aphasic symptoms. General hybrid accounts of this type have been put forth before by others, such as Murray (2002):

> Whereas aphasia has been traditionally viewed in terms of impairment of one or more language modalities, the attentional model of aphasia proposes that attention impairments can intensify or, under certain conditions, cause aphasic symptoms. This approach does not necessarily assert that all aphasic symptoms can be reduced to or explained by attention deficits but rather emphasizes the importance of determining which behaviors might be a product of attentional rather than purely linguistic factors (pp. 109–110).

Given positions of this type, it becomes important to find tractable ways to determine, if possible, the *specific* relationship between control operations and specific linguistic processes. In other words, it is important to determine whether a given deficit is caused by breakdowns in general cognitive control ability, breakdowns in specialized and automatic linguistic operations, or by a combination of these factors. Therefore, the following sections will outline research relevant to motivating a new model of this type. First, they will review research on executive control in semantic processing, followed by discussion of specific models of attention and cognitive control. These sections will lay the groundwork for the proposed model of cognitive control in aphasia that will follow.

## 2.5. Cognitive Control in Semantic Processing

So far, this discussion has been broad, focusing on the presence and role of attention and cognitive control in aphasia as a whole. However, it is important to reduce the scope of current project, as the locus of specific deficits may vary greatly by linguistic domain. For these reasons, the current project will address these questions at the lexical level.

Relevant research in this domain includes the work Lambon Ralph and colleagues, who have looked at the role of cognitive control in PWA with semantic deficits in a number of studies. One example of this work is Jefferies and Lambon Ralph (2006). In this case-series study, the authors compared 10 patients diagnosed with Semantic Dementia (SD) to 10 PWA with semantic deficits (all >1 year post CVA; 5 of these patients were classified as having transcortical sensory aphasia, while the rest were classified mixed, global, or conduction aphasia). All participants were tested on a series of measures characterizing working memory and executive ability, consisting of forwards and backwards digit span (Wechsler, 1987), the Visual Object and Space Perception battery (Warrington and James, 1991) and the Coloured Progressive Matrices test of non-verbal reasoning (Raven, 1962). PWA participants were also given the Wisconsin Card Sort test (WCS; Grant et al., 1948), the Brixton Spatial Rule Attainment task (Burgess and Shallice, 1996) and the Elevator Counting with and without distraction subtests from the TEA (Robertson et al., 1994) to further characterize attention and executive ability. All participants were also given a series of semantic assessments consisting of the Camel and Cactus Test (CCT; Bozeat et al., 2000), spoken word–picture matching, and spoken picture naming.

The authors found that although both groups possessed semantic deficits of similar severity, the pattern of results indicated qualitative differences in the underlying causes. SD patients demonstrated strong correlations between performance on all semantic tasks (CCT, word-picture matching, picture naming), high test-retest consistency for specific items, no significant relationships between semantic and cognitive performance, and performed much more accurately on high-frequency items, which the authors interpreted as evidence for an amodal semantic knowledge deficit. In contrast, PWA semantic performance correlated within task type, but not between task type, which the authors hypothesized was due to the differences in control demands required by different tasks. PWA did not show item frequency effects; instead the difficulty of establishing a specific semantic relationship or ruling out distracters (as rated in a separate norming study on healthy controls) predicted item accuracy. PWA also demonstrated impaired performance on all attention and executive tasks, and semantic performance was significantly correlated with performance on the Ravens and WCS executive tasks. The authors therefore concluded that semantic processing deficits in their PWA participants were caused by deficits in semantic control that negatively affected their ability to accurately access semantic representations in specific and task-relevant ways.

Lambon Ralph and colleagues have tested this semantic control deficit hypothesis using several other designs as well. Jefferies et al. (2008), found that when semantic aphasia and semantic dementia patients were given progressive phonemic cues, semantic aphasia patients were able to name most targets when cuing reached the point of uniquely identifying them, whereas semantic dementia patients only showed limited benefits of cuing on high-frequency pictures. The authors claimed that increasing cues raise the activation level for a target compared to distracters, and therefore this pattern of results also supports semantic control deficits in aphasia. Soni et al. (2009) also employed phonemic cuing using the same population, but in this study they contrasted correct word-initial phonemic cues against miscues corresponding to the first letter of category coordinates (e.g., if the target was ‘tiger’, the miscue would be ‘l’ corresponding to ‘lion’). They found that miscues resulted in an increase in error rates compared to correct cues, and a marginal increase compared to neutral cues (beeps). The magnitude of these effects was also significantly correlated with individual performance on executive function and attention measures (WCS, Brixton, TEA elevator counting without distraction). Again, this was interpreted at converging evidence in support of semantic control deficits, which impaired their ability to access specific semantic information in task-relevant ways.

Although these studies reported significant relationships between the extent of semantic control impairment and performance on general ‘nonlinguistic’ measures of attention and executive control, one issue that they did not directly address was the domain specificity of these control processes. In response, Hoffman et al. (2013) looked at the domain-specificity of semantic control in 3 PWA who had already been identified as possessing deficits of this type. They tested these patients and controls on a number of non-semantic linguistic control tasks intended to tax the executive components of shifting and updating (Miyake et al., 2000), including rhyme/phoneme judgment and working memory tasks (N-back, complex span with a dual task component, and alphabetical/

reverse letter list manipulation). They found that two of their patients did significantly worse than controls on all these tasks, but that the third patient only did worse than controls on alphabetizing letter lists. They claimed this task required a greater degree of semantic control than others (such as letters reversed), because it required the use of alphabetical knowledge to direct responses. The authors concluded that at least some aspects of semantic and general cognitive control are dissociable, and went on to tie this with functional localization work that argues for both specialized and "multiple demand" regions involved in semantic control in prefrontal and temporoparietal regions.

Hamilton and Martin (2005) also investigated the domain-specificity of cognitive control in PWA, focusing on inhibitory ability in a single patient with known semantic short-term memory deficits (patient “ML”). They tested this patient on both linguistic (Stroop, Recent Negatives) and nonlinguistic (Antisaccade, Nonverbal Stroop) tests of inhibitory function, which were all assumed to load on a single inhibition factor based on factor-analytic work in typical populations (Miyake et al., 2000). However, they found that ML presented with inhibition deficits in the semantic, but not perceptual domains, indicating at least some domain-specificity of semantic control functions.

So far, this review has focused primarily on the presence and potential role of attention and control deficits in aphasia, without making any great attempts to narrow the scope of discussion to specific aspects or models of attention or cognitive control. The following chapter will introduce a specific model of cognitive control originating in the working memory literature (i.e., Executive Attention; Kane and Engle, 2003), which will be the focus of the current work.

# CHAPTER 3

## Executive Attention

### 3.1. Models of Attention and Cognitive Control

So far, this review has focused primarily on the presence and potential role of attention and control deficits in aphasia, without making any great attempts to narrow the scope of discussion to specific aspects or models of attention or cognitive control. A specific model of cognitive control originating in the working memory literature will now be introduced, as its relation to aphasia will be investigated in the current project.

Engle and Kane (2004) presented a model of working memory that attempted to account for the strong positive correlations found between working memory ability and measure of fluid intelligence in the psychometric research. Although based on Baddeley's classic working memory work (e.g., Baddeley and Hitch, 1974), their model focused primarily on the "central executive" component of the model, claiming that this element of working memory accounted for the majority of individual differences in working memory capacity. Their version of working memory (first presented in Engle et al., 1999) consisted of 3 components:

1. Short-term memory, which consists of memory traces activated from LTM above a certain threshold, and in which some traces receive extra activation based on the focus of attention (Cowan, 1997).

2. Specific grouping, coding, and rehearsal skills and strategies for different

modalities, which may be more or less attention-demanding based on the task and amount of practice.

3. A central executive component which they labeled Executive Attention, defined as the ability to hold task related information in active memory, especially in the presence of interfering stimuli or information. They considered this component to be similar to the Supervisory Attention System of Norman and Shallice (1980). They claimed that this component maintained representations, goal abstractions, and stimulus-response mappings when these processes relied on controlled retrieval, and that as a construct, it overlapped heavily with the constructs of attention control, fluid intelligence (G*f*), working memory capacity, and models of prefrontal cortex functioning.

Engle and Kane further argued that the third component, Executive Attention, should be split into two interacting components: task maintenance and conflict resolution. Task maintenance refers to the ability to actively maintain goals and task sets in memory in such a way that they serve to guide and control behavior. This active maintenance is an effortful, resource-demanding endeavor. It is thought to involve, at a minimum, prefrontal cortex circuitry, which serves to strengthen task-relevant pathways and response mappings in a top-down fashion (Miller and Cohen, 2001). The authors state that the factor of task maintenance is also related to the concept of "Rule Working Memory" (e.g., Duncan, 2012), in that attention control processes serve to weight goal abstractions in the pursuit of goal attainment, especially in the context of novel tasks or in tasks that entail multiple response options. Impairments in this capacity, such as those experienced by individuals with frontal brain damage (Robertson et al., 1997) or low working memory capacity (Kane and Engle, 2003), can result in increased “goal neglect” during the pursuit of tasks, when individuals fail to respond in task-appropriate manner. Goal neglect can occur even when these individuals are able to explicitly state the intended goal, indicating that goal maintenance requires not only knowledge, but active control of the full task-dependent cognitive architecture implementing that knowledge (Engle and Kane, 2004). Although not explicitly stated, this factor also appears to be highly related to the construct of sustained attention (e.g., Posner and Peterson, 1990), with one important distinction: while sustained attention ability is generally assessed via simple monitoring tasks (e.g., tone discrimination, as per Erickson et al., 1996), task maintenance has been assessed specifically based on the ability to resolve conflict in the context of varying task maintenance demands, which reflects the proactive elements of this component (e.g., Kane and Engle, 2003; McVay & Kane, 2009; McVay & Kane, 2012).

The second factor in the Executive Attention model is conflict resolution, which is employed when resolving response competition, especially those caused by pre-potent activation patterns or habitual behaviors interfering with current task goals. Although the same basic factor is often referred to as inhibition (e.g., Miyake, 2000), Engle and Kane’s description was intentionally theory-neutral, as they claimed that most experimental manipulations are unable to distinguish between actual inhibition of information from increased activation of a target relative to distracters (Engle and Kane, 2004).

In the Executive Attention model, task maintenance and conflict resolution actively interact, in that the more actively task set is maintained, the easier it is to resolve any interference generated during the pursuit of task goals. One example the authors used to demonstrate this relationship is walking and driving for Americans visiting the UK. In both cases, individuals in the UK drive and walk on the left. Therefore, an American travelling there must constantly resolve the conflict that arises between the task set entailed by their current environment ("stay on the left") and their own habitual behaviors that are automatically cued by walking or driving ("stay on the right"). However, they claimed that these two activities differ greatly in goal maintenance demands: when driving, there a number of constant cues that serve to re-enforce the current task set (road signs, steering wheel position, etc.) whereas relatively few cues re-enforce task set when walking or crossing the street. This makes it much more demanding to actively maintain the novel task set while walking, and therefore results in increased conflict resolution demands and corresponding errors during this activity[2].

One way these researchers have investigated the relationship between task maintenance and conflict resolution is in the Stroop task (Stroop, 1935). The basic design has many forms (see MacLeod, 1991, for review), but the critical manipulation in these tasks are generally incongruent trials in which the subject is required to name the color a word is printed in while ignoring the written word itself (e.g., the word "green" written in

[2] This author recalls with humor and fondness his former college roommate, an exchange student from England, who was constantly bumping into other pedestrians as they walked together around the UMass Amherst campus.

red font), where producing a correct response requires inhibition/ conflict resolution. Engle and Kane (2004) stated that they became interested in this task because the literature appeared to be mixed regarding the role of prefrontal cortex damage on stroop performance: upon review, they observed that many of the studies with null findings for group differences had designs with either mostly or entirely incongruent word/color stimuli. When viewed in light of their 2-factor model of Executive Attention, they claimed that designs of this type minimized demands placed on goal maintenance, as every (or nearly-every) trial would therefore reinforce the novel task set, allowing it to become highly practiced and routinized. This in turn would greatly minimize the interference demands produced by the prepotent inclination to read the word. To test this, Kane and Engle (2003) looked at high and low working memory span subjects on a number of stroop tasks that manipulated the proportion of congruent vs. incongruent trials (e.g., 75% congruent vs. 0% congruent). They found that low-span subjects had a much harder time maintaining task set (as evidenced by accuracy rates on incongruent trials) compared to high span subjects in the mostly-congruent conditions, but not in mostly-incongruent conditions. They also noted faster response latencies for low-span subjects on congruent trials in the mostly-congruent conditions, which they interpreted as instances of ‘goal neglect’ where subjects covertly read the word, which is faster than naming a color. In addition, they found evidence for their predicted training effects on task maintenance: when subjects took a 75% congruent version of the task immediately following a 0% congruent version, accuracy differences between high and low-span groups disappeared, indicating that the 0% congruent condition had allowed subjects to practice the full task set and reduce demands on task maintenance. However, low-span subject still showed greater response-time interference effects in the 75% congruent condition, which the authors interpreted as evidence for residual conflict resolution difficulties, present even when goal maintenance was minimized.

### 3.2. Executive Attention in Aphasia

The executive model has been previously investigated in aphasia in one known instance. In unpublished dissertation research, Lim (2011) looked at whether PWA presented with impairments in executive attention in the semantic domain, in an attempt to better understand the nature of attention and resource-allocation deficits in this population. He tested 10 PWA and 20 unmatched controls (mean age for groups 58 and 65 years old, respectively). His primary measure was word-picture interference task in which subjects were required to make a semantic classifications (animal, non-animal) about words presented within pictures while ignoring the pictures' content. Incongruent trials consisted of a word presented within a picture from the alternate category (e.g., the word "Camel" presented within a picture of a table), neutral trials consisted of a word presented within a picture of a shape, while congruent trials consisted of a word presented within a picture of the word (e.g., the word "Camel" presented within a picture of a camel). This task therefore required subjects to resolve increased semantic interference in the incongruent compared to congruent and neutral conditions.

To look at goal maintenance, Lim manipulated the proportion of incongruent trials in 2 conditions, with a 19% incongruent condition and a 73% incongruent condition. He predicted that PWA would demonstrate impaired conflict resolution compared to controls as evidenced by an interaction effect between group and trial type, such that PWA would perform significantly worse in terms of error rates and reaction times on the incongruent trials across proportion manipulations, but would not differ from controls on the neutral and congruent trials. In addition, he predicted that PWA would also demonstrate impaired goal maintenance, which he claimed would be evidenced by an interaction effect between group and congruency proportion on incongruent trials, such that controls would perform worse in the 19% incongruent compared to 73% incongruent conditions, but that PWA would demonstrate equally poor performance across both these conditions:

> PWA will show no significant difference in RTs or error rates between two different proportions of incongruent conditions due to executive attention deficits in the PWA. However, NI [controls] will reveal significantly longer RTs and more errors in the 19% incongruent proportion than in the 73% incongruent proportion. There will be a significant interaction between groups and proportions of congruency on the PWI tasks in the incongruent conditions (Lim, 2011, p. 39).

Unfortunately, there were several interpretive and methodological issues with this study that limited the interpretability of results. First, his predictions for PWA in terms of goal maintenance is not in line Engle et al.'s model, as they argued that difficulty maintaining task goals should result in disproportionately poor performance on incongruent trials when incongruent trial occurred less frequently. However, Lim's prediction that PWA should show equally poor performance on incongruent trials regardless of trial proportion would not indicate difficulty in task maintenance, since task maintenance is facilitated by reinforcing cues: instead, this pattern of performance would indicate some manner of deficit in semantic control unaffected by task maintenance difficulty, or perhaps an inability to benefit from reinforcing cues in the 73% incongruent condition.

In addition to this infelicitous prediction, there were also discrepancies regarding reported results and their discussion, and issues with interpretation of statistical analyses. The major statistical concern was the fact that the author used post-hoc pair-wise comparisons to draw conclusions about differences in group performance when none of his primary analyses revealed significant group interactions. This issue was exacerbated by the fact that the study was underpowered. The author stated that to have power of .8 to detect interactions, he would have had to test 78 PWA instead of 10 (although he did not specify the estimates he used to produce these power calculations). In addition, control subjects were not matched to PWA subjects in terms of education or age, further complicating interpretation of results. Therefore, it is not possible to draw strong conclusions from this work about the presence of executive attention deficits in aphasia or their specific relationship to linguistic processes.

This being said, the author did make positive steps in seeking to investigate an important and understudied area, and some of the issues that come to the fore in the interpreting this work should be discussed. One such issue is the domain specificity of the systems involved. Executive attention ability was only tested in the context of a word-picture interference task, making it difficult to determine whether executive attention might be impaired across domains, or specifically impaired for semantic processing. The relation between this and previous background sections will now be discussed.

### 3.3. Domain-Specificity of Executive Attention

Engle and Kane (2004) claimed that the executive attention component of working memory is at least primarily a domain-general capacity. They claimed that when looking at the factor-analytic literature, many studies found that both verbal and visuo-spatial WM abilities loaded on a single factor, and in studies where 2-factor models presented better fits, these factors still tended to share more than 65% of their variance (Engle and Kane, 2004; p. 172). In their own work (Kane and Engle, 2003), they found a shared variance of 70% between spatial and verbal working memory factors in their most conservative analyses, and concluded that working memory capacity— and therefore in their model, executive attention— is largely general across these domains.

However, as has already been discussed, researchers have found dissociations in cognitive control abilities in PWA with semantic deficits (Hamilton and Martin, 2005; Hoffman et al., 2013). In the case of the Hamilton and Martin work, their patient was impaired on executive inhibitory measures that tapped semantic processes, but not visuo-spatial processes. In the Hoffman et al. work, they found that out of three PWA participants with identified semantic control deficits, one performed in the normal range on non-semantic working memory tasks, but that the other two were impaired in these processes. What is needed, then, is an account of how factors associated with cognitive control can clearly dissociate while at the same time tend to present as highly overlapping in latent variable work in healthy populations.

One possibility that will be discussed in detail in a subsequent section is that while conflict resolution may be domain-specific, task maintenance is not. The interactivity between these two factors tied with this formulation of domain-specificity could go a long ways towards accounting for the discrepancies between the factor-analytic and patient case study work. The reasoning behind this is as follows: since the level of active goal maintenance directly affects the demands placed on conflict resolution, a person with impairment in this ability will show greater interference effects across domains. In contrast, if conflict resolution/inhibition processes are to some extent dissociable (e.g., semantic vs. phonological or visuo-spatial control processes), then an individual might show greater interference effects in one domain but not another.

### 3.4. A Partial Encapsulation Account of Executive Attention in Aphasia

Earlier sections demonstrated a need for a hybrid account of aphasia, due to evidence for both selective linguistic and general cognitive impairments in this population. In order to develop a coherent account of this type, work by Lambon Ralph and colleagues was reviewed, who argued for an executive control-based account of semantic deficits for in PWA. This was followed by the introduction of Engle et al.'s Executive Attention model, with interacting components of task maintenance and conflict resolution. Specific claims about the domain-specificity of these systems were made, which will now be addressed in detail. What follows will be an attempt to tie together the following factors into one coherent picture: cognitive control (as reflected by task maintenance and conflict resolution), domain-specificity (for both control processes and automatic linguistic processes), and the impact of automaticity of function for each of these factors.

Task maintenance is the ability to generate and maintain novel task architectures and use them to exert proactive control that reduces interference demands during goal-directed processing. This likely occurs via a top-down strengthening of task-relevant pathways and attenuation of task-irrelevant pathways (Kiefer, 2012). The current claim is that this aspect of executive attention is a domain-general capacity, and that any task that either involves novel task architecture or has explicit goal states will draw on this capacity to some extent. However, this general system interacts with domain-specific operations (e.g., specialized linguistic and control operations), directly affecting the amount of interference encountered during the course of goal-directed linguistic processing.

In this account, deficits in task maintenance should cause control impairments across domains (e.g., semantic, phonological, visuospatial, etc.), because difficulty generating and actively maintaining task sets will increase conflict resolution demands regardless of modality. Therefore, PWA with impairments in goal maintenance should present with amodal control deficits.

Conflict resolution is the ability to resolve conflicts generated by interference during goal-directed processing. The current claim is that this capacity may be at least partially domain-specific, as this would go a long way towards accounting for control performance dissociations found in the literature (e.g., Hamilton and Martin, 2005; Hoffman et al., 2013). Since it is currently claimed that task maintenance is domain-general whereas conflict resolution is domain-specific (i.e., consisting of a set of encapsulated processes or capacities), this account will be referred to as the "partial-encapsulation account" of executive attention in aphasia.

Conceptualizing conflict resolution as a set of domain-internal processes has intuitive appeal, in that the same specialization that allows a system to represent and distinguish information within a specific modality may also provide it with the ability to handle interference generated specifically within that modality. Although the focus here is on cognitive control operations, this idea stems from a conceptualization of working memory put forward by Postle (2006): he claimed that working memory is an emergent property of the cognitive system that arises when specialized subsystems that handle the representation of specific information are recruited by prefrontal cortex attentional systems. If these attentional systems are responsible for task maintenance and the representational specialization of these subsystems also involves the ability to resolve domain-internal interference, then this model is completely consistent with the partial-encapsulation account proposed here.

If this formulation of conflict resolution is correct, then a PWA with a 'pure' deficit in this capacity should show increased interference effects even in contexts of minimal task maintenance demand, and these effects should be dissociable, with increased interference effects in one domain compared to others (e.g., specific linguistic domains compared to visuospatial domains).

Both of these executive attention components interact with specific specialized linguistic operations. For the purposes of the current framework, the majority of these linguistic operations are considered to be skilled and automatic, in that they are fast, generally processed in parallel, and automatically generated during ongoing cue-based memory retrieval. For example, in visual word recognition, operations of this type might include visual feature analysis, identification of letter units, activation of an orthographic input lexicon, and activation of the semantic system (Coltheart et al., 2001). The aspect critical to the current framework is that during the pursuit of goal-directed behavior, these individual processes are embedded within cognitive architectures of varying automaticity and control demands. Examples of goal-based visual word-recognition activities with differing task architectures might consist of lexical decision, reading single words aloud, or reading for pleasure.

In these goal-directed contexts, specialized linguistic operations are the content that task maintenance and conflict resolution act *upon*, and they do so in the fully interactive way outlined above. The added complication for a hybrid account of aphasia is that these specialized operations may themselves be specifically impaired, independently of control deficits. This has the potential to produce a number of complex interactions between levels. For example, changes in the amount or time-course of lexical activation may lead to more or less interference at key time points, or reduced automaticity of a given operation may lead to greater task maintenance demands.

Another complication is that although the partial-encapsulation account claims that task maintenance is a crucial domain-general capacity, task sets themselves can be habituated, at least to some extent (Engle and Kane, 2004). The more habituated a task set, the less it should draw on active task maintenance. Although of great importance, the specifics of this habituation process and its impact on language processing will have to remain largely outside the scope of the current work. Instead, this project will focus on tasks where crucial elements are not likely to be fully automated via habituation.

While this model may at first glance appear over-specified, with lesions at one or more levels of the system at times seeming to produce similar deficit patterns (e.g., a impairment in task maintenance ability contrasted against reduced automaticity of specific linguistic processes), this complexity is actually required based on the evidence for both selective impairments and general cognitive deficits in aphasia. Therefore, the aim of the current work is not to fully specify and substantiate every potential interaction at every level of this system, but instead to make principled claims about the role of the control components in such a way as to generate testable hypotheses.

As has been established, one reason to look at cognitive control in aphasia is that since these deficits have already been well-documented, it is necessary to determine exactly what role they play in language performance. However, a second reason that is of at least of equal importance is the fact that goal-based linguistic processing is crucial from a clinical perspective.

Not all processes that involve language are overtly goal-driven: for example, the internal monologue involved in mind-wandering is, almost by definition, language use without explicit goals. However, goal-driven processing represents a large and critical subset of language use, and this subset is most salient to PWA and clinicians alike. This is because PWA notice most acutely the functional linguistic breakdowns in which they had an explicit goal state that they were unable to attain (e.g., answer a question, describe an event). In a related vein, formal language testing focuses almost exclusively on various types of goal-based processing: without having explicit task instructions and goal states, it is almost impossible to generate objective criteria with which to assess performance. The role of control impairments in aphasia is therefore of great clinical concern.

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The next chapter will mark a shift in focus: up until now, literature has been reviewed in an attempt to motivate a specific model of cognitive control in aphasia at the lexical level of processing. Chapter 4 will instead outline a specific modeling method that will be useful for investigating the current claims.

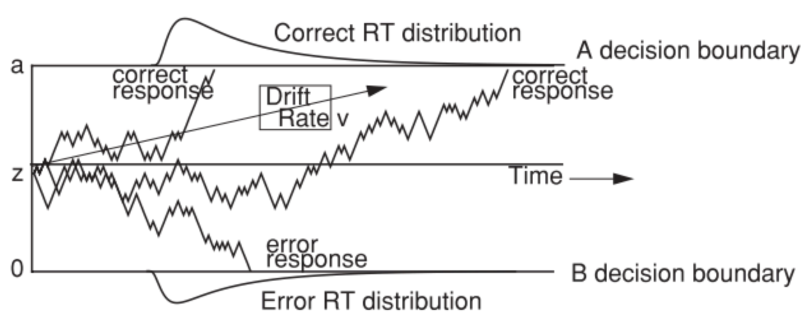
# CHAPTER FOUR

## The Diffusion Model

Given the current interest in the specific relationships between cognitive control and lexical processing, it is essential to characterize aspects of lexical processing in as much detail as possible. While behavioral research in the field of communication disorders has traditionally used response accuracy and reaction time as dependent variables that measure lexical processing, serial sequential sampling models such as the Diffusion Model (Ratcliff, 1978) present a powerful and well-validated means of extracting more detailed information about underlying components of language processing and decision making.

**Figure 4.1. Three simulated decision paths in the diffusion model with drift rate v, boundary width a, and starting point z.**

Reprinted from Ratcliff & McKoon, 2008.




The diffusion model assumes that decisions are made via a noisy process that slowly accumulates information over time, beginning at a starting point (*z*), and terminating in a response when it reaches one of two decision boundaries (*a* or 0)

(Ratcliff & McKoon, 2008). This accumulation of information is referred to as drift rate ($v$), with larger absolute values of this parameter associated with faster and more efficient accumulation of information (see figure 1). The two decision boundaries may vary in the model, indicating different thresholds to be reached prior to response initiation, and the absolute difference between these boundaries is referred to as boundary width ($a$).

The independence of drift rate and decision criteria allows the model to distinguish the efficiency of information extraction from the overall amount of information required before a decision is reached. This distinction can lead to a variety of relationships between accuracy and reaction time. For example, to reach a given decision boundary and corresponding level of accuracy, a smaller drift rate parameter will take much longer on average than a larger drift rate parameter. In contrast, if drift rates are held constant and boundary width is instead varied, a smaller boundary width will lead to faster responses but also lower levels of accuracy. The model not only accounts for the overall pattern of accuracy, speed, and related trade-offs, but also for the distribution of RTs in accurate and inaccurate responses in a given task.

In addition to drift rate and boundary separation, the model also includes parameters that characterize bias for one of the two responses ($z$), a nondecision component ($T_{er}$), which reflects operations that are independent of the decision process, such as early encoding or response output processes, and a number of parameters characterizing aspects of variability: $\eta$ is the standard deviation of the between-trial variability in drift rate, $s_z$ is the trail-to-trial variability in starting point, and $s_t$ reflects across trial variability in nondecision times.

Diffusion models have been successfully applied in a number of domains relevant to the current project, including lexical decision (Ratcliff et al., 2004a), individual differences (Ratcliff et al., 2010), clinical disorders (Ratcliff et al., 2004b), and semantic priming (Voss et al., 2013). In lexical decision, diffusion modeling has been shown to successfully model a wide range of known phenomena, with frequency effects mapping onto changes in drift rate ($v$), the proportion of word vs. nonword trials mapping on to changes in starting point (Ratcliff et al., 2004a), and the effects of task instruction or individual differences in age mapping onto changes in decision criteria boundary width (Wagenmakers et al., 2008).

In an example of the model applied to individual differences research, Ratcliff et al. (2010) tested the relationship between aging and IQ (as measured by matrix reasoning and vocabulary from the WAIS-III) on 3 tasks: numerosity discrimination, memory recognition, and lexical decision. They found that reaction time in all three tasks increased as age increased, but that there was minimal change in accuracy. Diffusion modeling showed that this pattern was observed because older subjects set wider decision criteria boundaries and had a large nondecision component, not because there were any age-related differences in underlying drift rates. More relevant to the current project, they also found that individual differences in IQ correlated moderately with drift rates in the lexical decision and memory recognition tasks, but only weakly with drift rates in the numerosity discrimination task, which they claimed drew less on high-level cognitive resources[3]. In contrast, IQ did not correlate with changes in boundary width or

[3] Ratcliff et al. point out that their IQ assessment consisted of matrix reasoning and vocabulary

nondecision components in any tasks with the exception of boundary width on numerosity discrimination, which they claimed was due to several outliers in their older subjects group. They also found no interactions between age and IQ on task performance on drift rates, which they interpreted as evidence against the cognitive reserve hypothesis (Satz, 1993).

The authors were also able to draw interesting conclusions about the relationship between reaction time and IQ. They stated that previous work had shown either conflicting or weak relationships between these factors. They claimed that was due to the uncorrelated relationship between drift rate, nondecision processing time, and boundary width during processing: although IQ affects drift rate and drift rate affects reaction time, nondecision processing and boundary width also directly affect reaction time independently, leading to a much weaker relationship IQ/RT relationship when looking across subjects compared to the strong relationship between IQ and drift rate. This is one demonstration of the model's advantages over simpler analyses, as it provides a level of granularity not available from approaches that analyze RT and accuracy independently.

To date, the model has only been applied to aphasia in one instance, Ratcliff, Perea, Colangelo, & Buchanan (2004). The authors applied the diffusion model to this population due to the observations that lexical decision performance in PWA is often quite good, although reaction times tend to be abnormally long and variable. The authors reanalyzed data previously reported in Moreno et al. (2002), which tested a total of 9

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subtests of the Wechsler Adult Intelligence Scale – 3rd Edition (WAIS-III; Wechsler, 1997), and therefore the relationship between IQ and drift rates in lexical decision may have been due to "crystalized intelligence" in the form of basic word knowledge, and not to fluid intelligence more directly related to the executive attention construct.

PWA (8 caused by left CVA, one by tumor treatment) on a written lexical decision task. They reported large differences in the nondecision component and boundary width and what they labeled as “relatively small” differences in drift rate between groups, with PWA shower more conservative boundary widths, larger nondecision components, and smaller drift rates.

Unfortunately, this study had several limitations. First, the relatively small number of trials in the experiment (74 high frequency words, 74 low-frequency words, and 148 nonwords) led to a corresponding small number of errors for high frequency words, which required combining data of individual participants into “super-subjects” to generate model parameters based on full distributions of accurate and inaccurate responses for each condition. Second, controls were not matched for age or education, making conclusions about age vs. pathology-related differences difficult to determine. Third, statistical comparisons could not be conducted between groups due to the small number of “super-subjects”, and therefore conclusions were based on qualitative comparisons of model parameters.

Although these considerations limit the strength of the conclusion that may be drawn from this study, it nonetheless clearly demonstrates the feasibility and potential usefulness of the diffusion modeling approach, especially if employed in experiments designed explicitly to allow from modeling at the individual level. The current study therefore uses diffusion modeling to improve the granularity of analysis in order to draw principled conclusions between aspects of lexical processing and cognitive control.

# CHAPTER 5

## Specific Aims and Study Predictions

Given the large and increasing costs of aphasia to society, it is important to improve our understanding of the cognitive-communication deficits experienced by persons with aphasia (PWA), as this understanding is crucial to developing more effective diagnostics and treatments. The preceding chapters have discussed an area of research relevant to this endeavor, namely the relationship between aphasia, language, and cognition. There is a growing body of research documenting attention and executive control impairments in PWA, but less work has been done to characterize the way in which these impairments relate to performance on linguistic tasks. To address this, the goal of this project is to investigate the relationship between executive attention and specific linguistic and control processes during goal-directed tasks.

Its central hypothesis is that PWA have impairments both in linguistic processing and in the mechanisms that control and efficiently utilize those processes, and that at least in some instances, these impairments are delineable. The basic rationale behind this claim is as follows: some PWA have been shown to have impairments in online processing relying on linguistic knowledge (e.g. Milberg & Blumstein, 1981). This has usually been taken as an indication that they have problems with a language processor, it has also been suggested that it instead reflects abnormal control of language processing (Hula & McNiel, 2008; Alexander, 2006; Jefferies & Lambon Ralph, 2006). This is consistent with the finding that PWA demonstrate impairments in attention and executive control (e.g., Murray, 2012). Therefore, the specific aims of the project were to investigate the role of executive function in linguistic deficits in PWA

The work to follow tested PWA and matched controls (MCs) on a set of six experiments to investigate the relationship between cognitive control, attention, and aphasia using a combination of behavioral experiments and a well-established mathematical model of the decision process.

The first four experiments were designed to characterize aspects of executive attention and sustained attention, in order to identify the aspects of these functions that affect the application of control during language processing. Experiments 1 and 2 tested executive attention and sustained attention using the Sustained Attention to Response (SART) go/no-go paradigm (Robertson et al., 1997), while experiments 3 and 4 relied on variations on the Stroop paradigm (Stroop, 1935) using word-picture interference and spatial interference. Experiments 1 and 3 required semantic classifications while experiments 2 and 4 required perceptual/visuospatial classifications.

The last two experiments investigated task adaption to varying speed and accuracy-focused contexts while processing lexical and nonlinguistic information. Experiment 5 used lexical decision, while experiment 6 used a numerosity judgment task. These experiments were designed to allow for the diffusion modeling to increase the granularity of analyses. Specific aims are as follows:

## 5.1 Aim 1: To characterize executive attention in PWA and document its relationship to controlled linguistic and nonlinguistic processing.

Participants were tested on a set of four experiments designed to measure executive function and attention in linguistic and nonlinguistic domains. In both domains, executive attention (Kane & Engle, 2003) and sustained attention were measured.

The proposed partial-encapsulation account of executive attention in aphasia claims that task maintenance and conflict resolution impairments are both present in PWA, but that task maintenance is a domain-general capacity whereas conflict resolution is at least partially domain-specific. Therefore, PWA should demonstrate worse performance than controls in both semantic (experiment 1: Semantic SART and experiment 3: Word-Picture Interference) and nonverbal (experiment 2: perceptual SART and experiment 4: Spatial Stroop) measures of task maintenance. In contrast, it is predicted that domain-specific conflict resolution deficits will cause PWA to demonstrate increased interference effects in the semantic but not nonverbal tasks.

Individual cases will also be examined for outliers in all tasks, using the criteria in Crawford & Howell (1998), which establish expected ranges of normal performance based on the mean, standard deviation, and number of control participants. It is expected that at least some PWA will demonstrate dissociations, with intact performance on nonverbal conflict resolution and impaired performance on semantic conflict resolution. However, given the claim that task maintenance is domain-general, individual PWA are not expected to show impairments in task maintenance in one domain but not the other.

## 5.2 Aim 2: To characterize the ability of PWA to adapt to variable task constraints during lexical decision and visuospatial tasks.

Participants were tested in a lexical decision experiment (experiment 5) in which aspects of control were manipulated by varying task instructions (neutral, speed emphasis, accuracy emphasis), while lower-level aspects of lexical processing were manipulated by varying word frequency (high, low). Participants were also tested in a similarly designed numerosity judgment experiment (experiment 6) in which aspects of control were manipulated by varying task instructions (neutral, speed emphasis, accuracy emphasis), while lower-level aspects of processing were manipulated based on discrimination difficulty (high, low). It is expected that PWA will show abnormal effects in control aspects of both tasks and in lower-level aspects of the lexical decision task.

In experiment 5, both controls and PWA should show effects of instructions and lexical frequency in RT, accuracy, and diffusion model parameters. Low frequency words should be associated with lower accuracy, higher RT and lower drift rates ($v$), and speed/accuracy instructions should affect boundary width, with a larger boundary width in the accuracy compared to speed instruction condition. When compared to controls, PWA are expected to show lower drift rates and larger nondecision components across conditions, and less of a change in boundary width between instruction conditions. PWA are also known to display highly variable performance: it is predicted that this will produce significantly larger between-trial variability in drift rates ($\eta$) when compared to MCs.

In experiment 6, both controls and PWA should show effects of instructions and numerosity discrimination difficulty in RT, accuracy, and diffusion model parameters. More difficult stimuli should be associated with lower accuracy, higher RT and lower drift rates (*v*), and speed/accuracy instructions should affect boundary width, with a larger boundary width in the accuracy compared to speed instruction condition. When compared to controls, PWA are not expected to show differences in drift rates or larger nondecision components across conditions. However, if adapting to shifting speed and accuracy task demands relies on general task maintenance, PWA should show the same difficulty adjusting boundary width that is predicted for experiment 5.

In addition, it is hypothesized that executive attention impairments in PWA negatively impact the ability to exert critical aspects of control involved in lexical processing. In experiment 5, it is hypothesized that generating and maintaining speed and accuracy priorities in response to varying task constraints requires task maintenance. Therefore, measures of executive attention ability from experiments 1 through 4 should predict the magnitude of changes in boundary width between the speed-focused and accuracy-focused conditions. Group differences in boundary width between conditions and group differences in $\eta$ are expected to be reduced when controlling for the effects of task maintenance ability. If the above reflects one instantiation of a general task adaption deficit, then the same patterns of results should be observed between executive attention measures and boundary width in experiment 6.

In addition, there is some evidence that drift rates can be affected by IQ (Ratcliff et al., 2010) and working memory (Schmiedek, Oberauer, Wilhelm, Süss, & Wittmann, 2007). If these effects are due to deployment of the central executive as measured by the executive attention model, then group differences in drift rates for experiment 5 should also be reduced when controlling for differences in task maintenance ability.

### 5.3 Summary of intended contributions

It is hoped that this project will improve our understanding of the relationship between attention, cognitive control, and lexical processing impairments in PWA, potentially leading to improved diagnostics and treatment. In the area of methods, it will also serve to validate the applicability of diffusion modeling in the field of communication disorders.

# CHAPTER SIX

## General Methods and Procedures

### 6.1. Equipment and testing environment

Participants were tested in quiet, well-lit testing room in the Language Science Lab at Boston University. All computer experiments were programmed in Psychopy version 1.78.01 (Peirce, 2007, 2008), and testing took place on Macintosh MacBook computers running OS X 10.6. All computer responses were collected via USB keyboard.

### 6.2. Duration and extent of individual participant involvement

Session one consisted of obtaining informed consent, collecting medical information, and standardized testing for PWA, while subsequent sessions consisted of experiment participation. For controls, session one consisted of informed consent, collection of medical information, cognitive screening, and experiment participation. Participants who completed the entire study were tested across 3 to 5 sessions each lasting 1–3 hours. PWA typically took 4 sessions to complete all testing while MCs typically took 3 sessions due to differences in speed of performance and group differences in the amount of screening and background testing.

Two executive attention tasks (experiments 1–4) were generally administered in one testing session, while experiments 5 and 6 were administered in separate testing sessions. Each participant was given all experiments in one of two orders, counterbalanced across participants:

**Order 1.** Experiment 3 (Word-Picture Interference), experiment 2 (perceptual SART), experiment 4 (Spatial Stroop), experiment 1 (semantic SART), experiment 6 (Numerosity), experiment 5 (Lexical Decision).

**Order 2.** Experiment 1 (semantic SART), experiment 4 (Spatial Stroop), experiment 2 (perceptual SART), Experiment 3 (Word-Picture Interference), experiment 5 (Lexical Decision), experiment 6 (Numerosity)

## 6.3. Participant Recruitment

PWA were recruited to participate in the study via the Boston University Aphasia Resource Center, fliers, word of mouth, and by referral from physicians and speech-language pathologists in the Boston area. Matched controls (MCs) were recruited to participate in the study by word-of-mouth, email, and online craigslist postings. Approximately half of the control group consisted of friends or family members of PWA involved in the Boston University Aphasia Resource Center.

## 6.4. Screening Procedures

During initial pre-consent contact, potential participants were told about the study and asked a series of eligibility questions to determine whether or not they qualified. If they passed this screening and stated they were interested in participating, they were scheduled for an initial session.

After informed consent was obtained, a medical questionnaire was completed and reviewed in detail to ensure that no eligibility criteria were missed in the initial screening phase. PWA participants also asked to sign a release form in order to allow access to neurological, neuropsychological, and speech-language pathology reports in their medical record, but this was not be a mandatory requirement for participation.

### 6.5. Eligibility Criteria

PWA and matched control participants were recruited between the ages of 30 and 80 years. PWA participants were required to have been diagnosed with aphasia following a stroke at least 6 months prior to study participation. Matched controls were selected such that average age and years of education were equivalent to the PWA group.

Only monolingual, English speakers were recruited for both groups, to control for potential attention and executive function differences in bilingual individuals. Control participants were tested for mild cognitive impairment and dementia using the Montreal Cognitive Assessment (MoCA; Nasreddine et al., 2005) and had to score in the normal range to participate in experiments.

For control participants, exclusionary criteria consisted of any acquired or degenerative neurological disorders known to cause cognitive or linguistic deficits (e.g., stroke, traumatic brain injury, Parkinson's disease), severe complicating concomitant medical conditions (e.g., major psychiatric illness), active medical problems that affected cognitive function (e.g., active cancer treatment), bilingualism, and a history or learning or language disabilities.

For PWA participants, exclusionary criteria were the same as above with the exception of stoke and aphasia (as outlined in the inclusionary criteria for this population). PWA participants were also assessed using a battery of standardized measures including the Cognitive-Linguistic Quick Test (CLQT). Participants who scored in the severely impaired range on this task were excluded from full battery participation, as it was predicted that they would not be able to tolerate and complete the full set of experiments.

PWA participant language performance was characterized based on the following tasks: the Cactus and Camel Test (CCT, Bozeat et al., 2000), the lexical decision and written word-picture matching subtests of the Psycholinguistic Assessment of Language Processing in Aphasia (PALPA; Kay et al., 1992), the Cognitive-Linguistic Quick Test (CLQT, Helm-Estabrooks, 2001), and the Philadelphia Naming Test- short form (PNT; Walker and Schwartz, 2012. PWA participants were video-recorded during these tasks to aid in scoring.

### 6.6. Informed Consent

For PWA participants, informed consent was obtained by the study PI, a certified speech-language pathologist. Once contact was established with a potential participant in this group, they were invited to discuss the experiment with their spouse/next of kin. The potential benefits and risks of the experiment as well as the general study procedures and level of involvement was explained to the patient and their family either in person or over the phone, and all parties were given the opportunity to ask questions. A copy of the consent form was provided, and they were given at least 24 hours to review it at their leisure, with the aid of the their spouse/next of kin if they wished. While obtaining informed consent, all information was reviewed verbally and in writing using language appropriate to the participants' comprehension ability to ensure they fully understood the extent of their involvement and their rights as a research participant.

For control participants, informed consent was also obtained by the study PI. They were given time to read the consent form at their own pace, and they were given the opportunity to ask questions prior to signing.

### 6.7. Protections Against Risk

This study obtained Boston University internal review (BU IRB protocol number 3192e). There were no physical, social, or legal risks associated with the participation in this study. Breaks were given during the assessment and treatment sessions in order to reduce the possibility of fatigue.

Participants were allowed to discontinue participation in the study at any time for any reason. Data was kept secured in locked file cabinets and password-secured servers, with subject identifiers kept separately from study data.

### 6.8. Potential Benefits of the Proposed Research and Payment

There were no direct benefits for individuals in this study. Because the research involved minimal risk to participants, the risks were deemed reasonable in relation to the anticipated benefits.

All participants were paid $10 per hour for their research participation.

# CHAPTER SEVEN

## Participants

### 7.1. Enrollment.

A total of 24 PWA were enrolled. Of these, 2 participants (PWA8 and PWA17) did not meet full eligibility requirements based on CLQT scores, and 20 PWA completed all study experiments[4]. A total of 29 MCs were also enrolled, 25 of which passed the screening and 23 of which completed all study experiments.

### 7.2. Demographics.

Table 7.1 lists PWA age, gender, total years of education, and handedness pre- and post-stroke. Table 7.2 lists PWA years post stroke-induced aphasia, and stroke, lesion, and diagnostic information where available. PWA demographic means, standard deviations, and ranges are compared against MC demographics in table 7.3 (note that MCs are well-matched to PWA for age and education, but not gender). Overall, the PWA sample was highly educated and heterogeneous in terms of stroke pathology and aphasia presentation.

### 7.3. Standard Aphasia Assessment.

PWA language performance was characterized based on the following tasks: the Cactus and Camel Test (CCT; Bozeat et al., 2000; table 7.4), the written lexical decision and written word-picture matching subtests of the PALPA (Kay et al., 1992; tables 7.5–

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[4] Participants PWA1, PWA2, MC1, and MC2 were part of an early experimental piloting phase, and only participated in experiments 1 through 4.

7.8), the Philadelphia Naming Test- short form A (PNT; Walker and Schwartz, 2012; table 7.9), and the Cognitive-Linguistic Quick Test (CLQT, Helm- Estabrooks, 2001; tables 7.10 and 7.11).

**Table 7.1. PWA demographics: gender, age, total years of education, and handedness pre- and post-stroke.**

| Participant | Gender | Age | Total Years of Education | Handedness Pre-Stroke | Current Handedness |
|---|---|---|---|---|---|
| PWA1 | M | 72 | 12 | Right | Right |
| PWA2 | M | 49 | 16 | Right | Left |
| PWA3 | M | 70 | 18 | Right | Right |
| PWA4 | M | 54 | 16 | Right | Left |
| PWA5 | M | 48 | 12 | Right | Left |
| PWA6 | M | 67 | 14 | Right | Left |
| PWA7 | M | 80 | 19 | Right | Right |
| PWA9 | M | 75 | 16 | Right | Left |
| PWA10 | F | 52 | 18 | Right | Left |
| PWA11 | M | 49 | 20 | Right | Right |
| PWA12 | M | 71 | 21 | Right | Right |
| PWA13 | M | 56 | 16 | Right | Right |
| PWA14 | M | 67 | 16 | Right | Left |
| PWA15 | F | 49 | 14 | Right | Left |
| PWA16 | M | 68 | 13 | Right | Left |
| PWA18 | M | 49 | 12 | Right | Right |
| PWA19 | F | 76 | 14 | Right | Left |
| PWA20 | F | 30 | 17 | Right | Left |
| PWA21 | M | 43 | 16 | Right | Right |
| PWA22 | M | 64 | 12 | Right | Right |
| PWA23 | F | 55 | 16 | Right | Right |
| PWA24 | F | 53 | 16 | Right | Right |

**Table 7.2. PWA, years post aphasia-inducing stroke, stroke and diagnostic information.**

| Participant | Years post aphasia | Stroke and diagnostic information |
|---|---|---|
| PWA1 | 4 | L CVA (ischemic); moderate-severe fluent aphasia. |
| PWA2 | 4 | L CVA (ischemic); moderate-to-severe nonfluent aphasia. |
| PWA3 | 2 | Multiple strokes. 1 LCVA 2012, 1 R CVA and 1 L CVA; mild anomic aphasia. |
| PWA4 | 5 | Multiple strokes. LCVA (left PCA) 2009 followed by subsequent R (temporoparietal); mild anomic aphasia. |
| PWA5 | 5 | L MCA CVA (ischemic; thalamic/ parietal); mild anomic aphasia and mild AOS. |
| PWA6 | 12 | LCVA (ischemic); severe nonfluent, severe AOS. |
| PWA7 | 8 | L CVA (ischemic); mild anomic aphasia. |
| PWA9 | 2.5 | TIA/L CVA (ischemic, carotid artery); mod-severe nonfluent transcortical motor. |
| PWA10 | 4.5 | AVM/ L CVA (hemorrhage), frontoparietal; anomic aphasia. |
| PWA11 | 5 | L MCA CVA (ischemic); mild nonfluent aphasia. |
| PWA12 | 10 | Multiple strokes, starting in 1999 (6 total); aphasia following L CVA (ischemic) 2004. |
| PWA13 | 2 | L MCA CVA (ischemic), frontal, temporal, parietal; anomic aphasia. |
| PWA14 | 11 | L CVA (ischemic), parietal (Wernicke's area), mild fluent aphasia. |
| PWA15 | 3 | AVM/ L CVA (hemorrhage); severe nonfluent aphasia. |
| PWA16 | 7 months | Single CVA, location unknown; mild fluent aphasia. |
| PWA18 | 3.5 | L MCA (superior division) CVA (hemorrhage), affected insula and temporal lobe. |
| PWA19 | 4 | L MCA CVA (hemorrhage); mild-mod receptive/expressive aphasia. |
| PWA20 | 4 | L MCA CVA (parietal, ischemic); moderate-severe nonfluent. |
| PWA21 | 1.5 | L Carotid CVA. Mild fluent. |
| PWA22 | 7 months | L MCA CVA (ischemic), temporoparietal and subcortical. |
| PWA23 | 2 | L MCA CVA (ischemic). |
| PWA24 | 7 | L CVA (ischemic, carotid artery). |

**Table 7.3. Comparison of PWA and MC group demographics. Mean, standard deviation, and range for age and years of education, proportion of gender and handedness pre-stroke.**

| | | PWA | MC |
|---|---|---|---|
| Age | Mean | 59.0 | 59.3 |
| | SD | 12.7 | 13.2 |
| | Range | 30 to 80 | 28 to 80 |
| Education | Mean | 15.6 | 15.7 |
| | SD | 2.6 | 2.3 |
| | Range | 12 to 21 | 12 to 19 |
| Handedness | (Total right, left) | 20, 0 | 23, 2 |
| Gender | (Total male, female) | 14, 6 | 5, 20 |

**Table 7.4. PWA performance on the Cactus and Camel Test (CCT; Bozeat et al., 2000).**

| | Total correct (64) | living (32) | manmade (32) | domestic animals (8) | birds (8) | large household items (8) | vehicles (8) | foreign animals (8) | fruit (8) | small household items (8) | tools (8) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PWA1 | 33 | 14 | 19 | 4 | 3 | 5 | 5 | 3 | 4 | 3 | 6 |
| PWA2 | 38 | 17 | 21 | 6 | 4 | 5 | 6 | 5 | 2 | 4 | 6 |
| PWA3 | 52 | 25 | 27 | 7 | 4 | 6 | 8 | 7 | 7 | 7 | 6 |
| PWA4 | 51 | 27 | 24 | 8 | 7 | 5 | 6 | 5 | 7 | 7 | 6 |
| PWA5 | 57 | 30 | 27 | 8 | 7 | 7 | 7 | 8 | 7 | 6 | 7 |
| PWA6 | 50 | 24 | 26 | 8 | 6 | 6 | 6 | 6 | 4 | 8 | 6 |
| PWA7 | 44 | 19 | 25 | 5 | 7 | 6 | 8 | 4 | 3 | 6 | 5 |
| PWA9 | 50 | 23 | 27 | 7 | 5 | 7 | 6 | 6 | 5 | 7 | 7 |
| PWA10 | 55 | 27 | 28 | 7 | 7 | 7 | 7 | 8 | 5 | 7 | 7 |
| PWA11 | 55 | 28 | 27 | 8 | 7 | 6 | 7 | 7 | 6 | 8 | 6 |
| PWA12 | 28 | 19 | 9 | 5 | 3 | 1 | 5 | 5 | 6 | 2 | 1 |
| PWA13 | 61 | 30 | 31 | 8 | 6 | 8 | 8 | 8 | 8 | 8 | 7 |
| PWA14 | 46 | 24 | 22 | 6 | 5 | 3 | 6 | 7 | 6 | 6 | 7 |
| PWA15 | 50 | 23 | 27 | 7 | 5 | 6 | 6 | 6 | 5 | 8 | 7 |
| PWA18 | 54 | 25 | 29 | 8 | 6 | 8 | 7 | 6 | 5 | 8 | 6 |
| PWA19 | 49 | 25 | 24 | 8 | 6 | 7 | 6 | 6 | 5 | 6 | 5 |
| PWA20 | 52 | 25 | 27 | 8 | 5 | 5 | 8 | 6 | 6 | 8 | 6 |
| PWA21 | 58 | 29 | 29 | 8 | 7 | 7 | 7 | 7 | 7 | 7 | 8 |
| PWA23 | 49 | 22 | 27 | 7 | 5 | 8 | 5 | 5 | 5 | 6 | 8 |
| PWA22 | 50 | 23 | 27 | 8 | 4 | 6 | 6 | 6 | 5 | 8 | 7 |
| PWA16 | 59 | 29 | 30 | 8 | 7 | 7 | 8 | 8 | 6 | 8 | 7 |
| PWA24 | 57 | 25 | 32 | 6 | 7 | 4 | 6 | 7 | 5 | 8 | 5 |
| Group mean | 49.9 | 24.2 | 25.7 | 7.0 | 5.6 | 5.9 | 6.5 | 6.2 | 5.4 | 6.6 | 6.2 |
| Group sd | 8.2 | 4.2 | 4.8 | 1.2 | 1.4 | 1.7 | 1.0 | 1.3 | 1.4 | 1.7 | 1.4 |

Note: Total number of items per test/subtest in parentheses.

**Table 7.5. PWA performance on written lexical decision (PALPA 24): illegal nonwords (Kay et al., 1992).**

| | Total correct (60) | regular words (15) | exception words (15) | nonwords (30) |
|---|---|---|---|---|
| PWA1 | 43 | 9 | 12 | 22 |
| PWA2 | 51 | 10 | 11 | 30 |
| PWA3 | 60 | 15 | 15 | 30 |
| PWA4 | 57 | 15 | 12 | 30 |
| PWA5 | 60 | 15 | 15 | 30 |
| PWA6 | 58 | 15 | 14 | 29 |
| PWA7 | 60 | 15 | 15 | 30 |
| PWA9 | 60 | 15 | 15 | 30 |
| PWA10 | 56 | 14 | 14 | 28 |
| PWA11 | 60 | 15 | 15 | 30 |
| PWA12 | 58 | 15 | 15 | 28 |
| PWA13 | 60 | 15 | 15 | 30 |
| PWA14 | 60 | 15 | 15 | 30 |
| PWA15 | 59 | 15 | 14 | 30 |
| PWA18 | 60 | 15 | 15 | 30 |
| PWA19 | 59 | 15 | 15 | 29 |
| PWA20 | 59 | 15 | 14 | 30 |
| PWA21 | 60 | 15 | 15 | 30 |
| PWA23 | 59 | 15 | 14 | 30 |
| PWA22 | 57 | 12 | 15 | 30 |
| PWA16 | 59 | 14 | 15 | 30 |
| PWA24 | 59 | 15 | 14 | 30 |
| Group mean | 57.9 | 14.3 | 14.3 | 29.4 |
| Group sd | 3.9 | 1.7 | 1.2 | 1.8 |

Note: Total number of items per test/subtest in parentheses.

**Table 7.6. PWA performance on written lexical decision (PALPA 25): imageability/ frequency (Kay et al., 1992).**

| | Total correct (120) | HI/HF (15) | HI/LF (15) | LI/HF (16) | LI/LF (14) | Nonwords (60) |
|---|---|---|---|---|---|---|
| PWA1 | 69 | 10 | 10 | 6 | 5 | 38 |
| PWA2 | 98 | 13 | 14 | 8 | 10 | 53 |
| PWA3 | 120 | 15 | 15 | 15 | 15 | 60 |
| PWA4 | 98 | 12 | 13 | 13 | 10 | 50 |
| PWA5 | 120 | 15 | 15 | 15 | 15 | 60 |
| PWA6 | 86 | 14 | 15 | 14 | 14 | 29 |
| PWA7 | 111 | 14 | 15 | 15 | 15 | 52 |
| PWA9 | 120 | 15 | 15 | 16 | 14 | 60 |
| PWA10 | 119 | 15 | 15 | 16 | 14 | 59 |
| PWA11 | 120 | 15 | 15 | 15 | 15 | 60 |
| PWA12 | 113 | 15 | 15 | 15 | 12 | 56 |
| PWA13 | 106 | 15 | 14 | 15 | 14 | 48 |
| PWA14 | 111 | 15 | 14 | 15 | 15 | 52 |
| PWA15 | 85 | 15 | 14 | 14 | 13 | 28 |
| PWA18 | 119 | 15 | 15 | 16 | 13 | 60 |
| PWA19 | 113 | 15 | 15 | 16 | 14 | 53 |
| PWA20 | 116 | 15 | 14 | 16 | 13 | 58 |
| PWA21 | 114 | 14 | 15 | 16 | 13 | 56 |
| PWA23 | 118 | 15 | 15 | 16 | 13 | 59 |
| PWA22 | 110 | 14 | 15 | 16 | 11 | 54 |
| PWA16 | 112 | 15 | 14 | 16 | 12 | 55 |
| PWA24 | 113 | 15 | 15 | 16 | 12 | 55 |
| Group mean | 108.7 | 14.4 | 14.4 | 14.5 | 12.8 | 52.5 |
| Group sd | 13.6 | 1.3 | 1.1 | 2.6 | 2.3 | 9.3 |

Note: Total number of items per test/subtest in parentheses.

**Table 7.7. PWA performance on written lexical decision (PALPA 26): morphology (Kay et al., 1992).**

| | Total correct (60) | regularly inflected (15) | derivational (15) | nonword (30) |
|---|---|---|---|---|
| PWA1 | 35 | 9 | 10 | 16 |
| PWA2 | 40 | 8 | 8 | 24 |
| PWA3 | 58 | 15 | 15 | 28 |
| PWA4 | 51 | 14 | 14 | 23 |
| PWA5 | 55 | 15 | 15 | 25 |
| PWA6 | 36 | 15 | 14 | 7 |
| PWA7 | 46 | 14 | 14 | 18 |
| PWA9 | 56 | 14 | 14 | 28 |
| PWA10 | 58 | 15 | 15 | 28 |
| PWA11 | 54 | 15 | 15 | 24 |
| PWA12 | 56 | 12 | 14 | 30 |
| PWA13 | 51 | 14 | 14 | 23 |
| PWA14 | 50 | 15 | 15 | 20 |
| PWA15 | 35 | 15 | 13 | 7 |
| PWA18 | 58 | 14 | 15 | 29 |
| PWA19 | 54 | 14 | 15 | 25 |
| PWA20 | 50 | 14 | 15 | 21 |
| PWA21 | 43 | 15 | 14 | 14 |
| PWA23 | 45 | 14 | 15 | 16 |
| PWA22 | 55 | 15 | 15 | 25 |
| PWA16 | 55 | 14 | 15 | 26 |
| PWA24 | 52 | 13 | 13 | 26 |
| Group mean | 49.7 | 13.8 | 14.0 | 22.0 |
| Group sd | 7.6 | 1.9 | 1.8 | 6.5 |

Note: Total number of items per test/subtest in parentheses.

**Table 7.8. PWA performance on written word-picture matching (PALPA 48; Kay et al., 1992).**

| | Total correct (40) | close semantic | distant semantic | visual | unrelated |
|---|---|---|---|---|---|
| PWA1 | 18 | 10 | 4 | 4 | 4 |
| PWA2 | 21 | 8 | 7 | 4 | 0 |
| PWA3 | 40 | 0 | 0 | 0 | 0 |
| PWA4 | 39 | 0 | 1 | 0 | 0 |
| PWA5 | 40 | 0 | 0 | 0 | 0 |
| PWA6 | 32 | 3 | 2 | 2 | 1 |
| PWA7 | 39 | 1 | 0 | 0 | 0 |
| PWA9 | 40 | 0 | 0 | 0 | 0 |
| PWA10 | 39 | 0 | 0 | 1 | 0 |
| PWA11 | 40 | 0 | 0 | 0 | 0 |
| PWA12 | 40 | 0 | 0 | 0 | 0 |
| PWA13 | 39 | 1 | 0 | 0 | 0 |
| PWA14 | 40 | 0 | 0 | 0 | 0 |
| PWA15 | 18 | 4 | 7 | 7 | 4 |
| PWA18 | 39 | 0 | 0 | 1 | 0 |
| PWA19 | 38 | 2 | 0 | 0 | 0 |
| PWA20 | 40 | 0 | 0 | 0 | 0 |
| PWA21 | 40 | 0 | 0 | 0 | 0 |
| PWA23 | 39 | 0 | 0 | 0 | 1 |
| PWA22 | 38 | 1 | 1 | 0 | 0 |
| PWA16 | 8 | 9 | 5 | 9 | 9 |
| PWA24 | 39 | 0 | 0 | 1 | 0 |
| Group mean | 34.8 | 1.8 | 1.2 | 1.3 | 0.9 |
| Group sd | 9.4 | 3.1 | 2.3 | 2.5 | 2.2 |

Note: Total number of items per test/subtest in parentheses.

**Table 7.9. PWA performance on Philadelphia Naming Test- short form (PNT; Walker and Schwartz, 2012).**

| | Total correct (30) |
|---|---|
| PWA1 | 10 |
| PWA2 | 2 |
| PWA3 | 30 |
| PWA4 | 22 |
| PWA5 | 30 |
| PWA6 | 10 |
| PWA7 | 8 |
| PWA9 | |
| PWA10 | 30 |
| PWA11 | 30 |
| PWA12 | 29 |
| PWA13 | 30 |
| PWA14 | 27 |
| PWA15 | 0 |
| PWA18 | 30 |
| PWA19 | 18 |
| PWA20 | 27 |
| PWA21 | 19 |
| PWA23 | 21 |
| PWA22 | 6 |
| PWA16 | 30 |
| PWA24 | 27 |
| Group mean | 21.8 |
| Group sd | 9.6 |

Note: total number of test items in parentheses. Testing discontinued for PWA15 on this test on item 21 due to frustration and difficulty.

**Table 7.10. PWA performance for subtests on the Cognitive-Linguistic Quick Test (CLQT, Helm-Estabrooks, 2001).**

| | personal facts (8) | symbol cancellation (12) | confrontation naming (10) | clock drawing (13) | story retelling (10) | symbol trials (10) | generative naming (9) | design memory (6) | mazes (8) | design generation (13) |
|---|---|---|---|---|---|---|---|---|---|---|
| PWA1 | 0 | 8 | 5 | 7 | 2 | 3 | 1 | 6 | 8 | 9 |
| PWA2 | 0 | 8 | 0 | 11 | 0 | 5 | 1 | 6 | 8 | 0 |
| PWA3 | 8 | 12 | 10 | 13 | 8 | 5 | 2 | 6 | 7 | 2 |
| PWA4 | 8 | 0 | 9 | 9 | 11 | 7 | 4 | 5 | 6 | 4 |
| PWA5 | 8 | 12 | 10 | 13 | 5 | 10 | 3 | 6 | 8 | 6 |
| PWA6 | 2 | 12 | 7 | 13 | 4 | 10 | 5 | 6 | 8 | 8 |
| PWA7 | 6 | 0 | 10 | 1 | 4 | 10 | 7 | 5 | 7 | 1 |
| PWA9 | 7 | 11 | 10 | 11 | 3 | 10 | 3 | 6 | 4 | 4 |
| PWA10 | 8 | 12 | 10 | 13 | 10 | 10 | 5 | 6 | 8 | 7 |
| PWA11 | 8 | 12 | 10 | 13 | 6 | 10 | 6 | 6 | 8 | 7 |
| PWA12 | 6 | 12 | 10 | 7 | 1 | 10 | 2 | 6 | 4 | 5 |
| PWA13 | 8 | 12 | 10 | 13 | 4 | 10 | 3 | 6 | 8 | 7 |
| PWA14 | 8 | 12 | 10 | 10 | 4 | 10 | 2 | 6 | 8 | 6 |
| PWA15 | 0 | 12 | 1.5 | 10 | 1 | 10 | 0 | 4 | 8 | 5 |
| PWA18 | 8 | 12 | 10 | 13 | 3 | 10 | 4 | 6 | 8 | 7 |
| PWA19 | 3 | 2 | 8 | 9 | 5 | 2 | 2 | 4 | 4 | 6 |
| PWA20 | 8 | 12 | 10 | 13 | 7 | 8 | 4 | 6 | 8 | 7 |
| PWA21 | 8 | 12 | 7 | 13 | 7 | 10 | 4 | 6 | 8 | 9 |
| PWA23 | 8 | 12 | 10 | 11 | 4 | 8 | 2 | 5 | 4 | 6 |
| PWA22 | 7 | 12 | 5 | 10 | 4 | 8 | 2 | 6 | 4 | 5 |
| PWA16 | 8 | 11 | 10 | 11 | 11 | 10 | 5 | 4 | 8 | 7 |
| PWA24 | 8 | 12 | 10 | 11 | 6 | 10 | 4 | 6 | 7 | 4 |
| Group mean | 6.1 | 10.0 | 8.3 | 10.7 | 5.0 | 8.5 | 3.2 | 5.6 | 6.9 | 5.5 |
| Group sd | 3.0 | 4.0 | 2.9 | 2.9 | 3.1 | 2.5 | 1.7 | 0.7 | 1.7 | 2.3 |

Note: Maximum subtest score in parentheses.

**Table 7.11. PWA performance for composite scores on the Cognitive-Linguistic Quick Test (CLQT, Helm-Estabrooks, 2001).**

| | attention | attention severity | memory | memory severity | executive function (EF) | EF severity | language | language severity | visuospatial | visuospatial severity | clock drawing | clock drawing severity | severity composite |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PWA1 | 138 | 3 | 73 | 1 | 21 | 4 | 8 | 1 | 79 | 4 | 7 | 2 | 2.60 |
| PWA2 | 131 | 2 | 61 | 1 | 14 | 1 | 1 | 1 | 74 | 3 | 11 | 4 | 1.60 |
| PWA3 | 181 | 4 | 166 | 4 | 16 | 3 | 28 | 4 | 81 | 4 | 13 | 4 | 3.80 |
| PWA4 | 81 | 2 | 176 | 4 | 21 | 3 | 32 | 4 | 56 | 3 | 9 | 3 | 3.20 |
| PWA5 | 198 | 4 | 149 | 3 | 27 | 4 | 26 | 3 | 98 | 4 | 13 | 4 | 3.60 |
| PWA6 | 198 | 4 | 103 | 1 | 31 | 4 | 18 | 1 | 100 | 4 | 13 | 4 | 2.80 |
| PWA7 | 77 | 2 | 123 | 3 | 25 | 4 | 27 | 3 | 62 | 4 | 1 | 1 | 3.20 |
| PWA9 | 167 | 4 | 130 | 3 | 21 | 4 | 23 | 2 | 82 | 4 | 11 | 4 | 3.40 |
| PWA10 | 209 | 4 | 181 | 4 | 30 | 4 | 33 | 4 | 99 | 4 | 13 | 4 | 4.00 |
| PWA11 | 201 | 4 | 158 | 4 | 31 | 4 | 30 | 4 | 99 | 4 | 13 | 4 | 4.00 |
| PWA12 | 173 | 3 | 110 | 2 | 21 | 3 | 19 | 1 | 85 | 4 | 7 | 4 | 2.60 |
| PWA13 | 197 | 4 | 143 | 3 | 28 | 4 | 25 | 3 | 99 | 4 | 13 | 4 | 3.60 |
| PWA14 | 196 | 4 | 142 | 3 | 26 | 4 | 24 | 2 | 98 | 4 | 10 | 3 | 3.40 |
| PWA15 | 185 | 4 | 46 | 1 | 23 | 3 | 2.5 | 1 | 89 | 4 | 10 | 3 | 2.60 |
| PWA18 | 195 | 4 | 138 | 2 | 29 | 4 | 25 | 3 | 99 | 4 | 13 | 4 | 3.40 |
| PWA19 | 64 | 2 | 93 | 2 | 14 | 3 | 18 | 2 | 42 | 3 | 9 | 3 | 2.40 |
| PWA20 | 197 | 4 | 162 | 4 | 27 | 4 | 29 | 4 | 95 | 4 | 13 | 4 | 4.00 |
| PWA21 | 205 | 4 | 162 | 4 | 31 | 4 | 26 | 3 | 101 | 4 | 13 | 4 | 3.80 |
| PWA23 | 172 | 3 | 132 | 2 | 20 | 3 | 24 | 2 | 78 | 3 | 11 | 4 | 2.60 |
| PWA22 | 173 | 3 | 135 | 2 | 19 | 2 | 18 | 1 | 81 | 3 | 10 | 3 | 2.20 |
| PWA16 | 198 | 4 | 167 | 4 | 30 | 4 | 34 | 4 | 89 | 3 | 11 | 4 | 3.80 |
| PWA24 | 194 | 4 | 156 | 4 | 25 | 4 | 28 | 3 | 93 | 4 | 11 | 3 | 3.80 |
| Group mean | 169.5 | 3.5 | 132.1 | 2.8 | 24.1 | 3.5 | 22.7 | 2.5 | 85.4 | 3.7 | 10.7 | 3.5 | 3.2 |
| Group sd | 43.7 | 0.8 | 37.3 | 1.2 | 5.5 | 0.8 | 9.0 | 1.2 | 15.8 | 0.5 | 2.9 | 0.8 | 0.7 |

Note: Severity ratings on a 1–4 scale; 1= “severely impaired”, 2= “moderately impaired”, 3= “mildly impaired”, and 4 = “within normal limits”.

# CHAPTER EIGHT

## Experiment 1: Semantic Sustained Attention to Response

### 8.1. Methods and Procedure for Experiment 1

#### *8.1.1. Materials and Design*

The Sustained Attention to Response (SART) paradigm was originally developed by Robertson et al. (1997), and has been shown to be sensitive to attention impairments following traumatic brain injury. Experiment 1 used this paradigm and followed the basic methodology of McVay and Kane (2009) and McVay and Kane (2012). In the task, participants were asked to classify a series of visually presented words (animal words and food words) via key press in a go/no-go design. This task was presented in two conditions, one with low executive attention demand (Low EA), and one with high executive attention demand (High EA).

In both conditions, animals (e.g., "blujay") were presented on 89% of trials and food (e.g., "granola") on 11% of trials. In the Low EA condition, a key press (the space bar) was required in response to the infrequent category (food), making this essentially a test of sustained attention without any required prepotent response inhibition. In contrast, in the High EA condition, participants were asked to respond to the frequent category (animal) and withhold their response when presented with the infrequent category (food). This second condition requires suppressing the established response activity (i.e., the habituated response generated by a key press on 89% of trials), and therefore taxed executive attention more than the first. Stimuli were presented in black text on a white background on an LCD laptop monitor and responses were recorded on an external USB keyboard.

Overall, experiment 1 employed a 2x2x2 mixed factorial design, with semantic category (animal, food) and executive attention demand (High vs. Low EA) as within-subject factors, and group (PWA vs. matched control) as a between-subject factor.

### *8.1.2. Procedure*

A total of 550 trials were presented in this task, split evenly between Low EA and High EA conditions. In each EA condition, 225 trials were presented in five consecutive blocks without breaks. Each block used the same list of 45 words, 40 animal words and five plant-based food words, with presentation order randomized within each block[5].

Participants were each presented with the Low EA condition blocks first, followed by the High EA condition blocks, and participants were given the option to take a short break between conditions. Although this design decision potentially conflates fatigue with executive attention demand, it also holds the effect of task order and practice constant across participants and ensures that the Hard EA condition was maximally demanding.

In the version of this task employed by McVay and Kane, each word was

[5] McVay and Kane (2012) presented a total of 4 lists of unique animal and food words each repeated five times, for a total of 1800 stimuli per condition. Given the reduced length of the current experiment, only one of these word lists was selected.

presented for 300 ms, followed by a 900 ms pattern mask, for a total trial duration of 1200 ms. An initial version of the current experiment was created using these presentation durations and piloted on 8 college-aged controls and 2 participants with aphasia (PWA1 and PWA2). Although the controls showed expected effects of condition, neither participant with aphasia were able to initiate responses within this time window for the infrequent category in the Low EA condition, with 0% accuracy for both PWA on this category. Therefore, the design was modified by extending presentation durations, with each word was presented for 600 ms, followed by a 1900 ms pattern mask of 12 "#" signs. A 10 ms inter-trial interval was also added in order to facilitate the loading and accurate timing of image presentation, resulting in a full 2500 ms between the onset of each new trial.

Each condition was preceded by a set of written instructions that were read to each participant, followed by two rounds of practice using an unrelated word list of 12 items (3 were food words and 9 were animal words). To ensure equal task comprehension across participants, PWA were given the option to take two additional rounds of practice if needed. If these additional rounds of practice were requested, they were also given optional offline practice and additional instruction using index cards and an unplugged keyboard to ensure basic ability to make semantic classifications of this type and retain the stimulus/response mappings in an untimed context. All participants were asked to focus on both speed and accuracy in their responses.

In the Low EA condition, performance was interpreted as a measure of sustained attention given the demands placed on task maintenance in the relative absence of interference. In the High EA condition, it was interpreted as a measure of executive attention based on the combined requirements of maintaining task set while resolving interference generated by motor habituation.

## 8.2. Statistical Techniques

With the exception of the signal sensitivity scores to be described in the next section, analyses of all repeated measures data followed the general methods of Evans et al. (2015), which are excerpted as follows:

> Accuracy and reading time data were analyzed using linear mixed-effects models with crossed subject and item random effects. This class of models (also at times referred to as "hierarchical regression" or "multilevel regression") has recently been gaining popularity in psycholinguistics research as an alternative to repeated-measures analysis of variance (ANOVA). In the traditional repeated-measures ANOVA approach (Clark, 1973), fixed effects of interest […] are evaluated in two separate models: one with by subject random effects ($F_1$) and a second with by item random effects ($F_2$). The first allows generalization from the subject sample to the general population, while the second allows generalization to the population of items (in this case, all possible words or sentences with the same properties). The two models are then crossed via a statistic such as min-$F$ or merely treated as independent tests of significance ($F_1$ x $F_2$; Barr, Levy, Scheepers, & Tily, 2013). In contrast, mixed-effects models allow simultaneous modeling of these random subject and item effects and cross them in a single

model, making both subject and item-specific adjustments to estimates at the level of individual trial data (Baayen, Davidson, & Bates, 2008). They possess a number of advantages: they are a form of generalized linear model, and therefore allow the use of continuous variables for fixed effects instead of requiring categorical grouping variables for measures such as ST–WM; they allow better handling of binary outcome variables via logistic regression techniques (Jaeger, 2008); they are more robust to missing data and unbalanced designs (Baayen et al., 2008); finally, they may be more powerful than traditional techniques when their random effects are appropriately specified (Barr et al., 2013).

(…)In addition to standard *p* values, we also report likelihood ratios ("bits of evidence") for models that tested for interaction effects, per the methods of Lawrence and Klein (2013). These ratios are generated by calculating AIC-adjusted likelihoods for each model of interest and its restricted counterpart (i.e., the same model run without the fixed effect interaction term), then calculating the likelihood ratio and converting to log-base-2 scale. Lawrence and Klein stated that a positive ratio may be interpreted as evidence for the interaction, while a negative ratio was evidence for a null effect. While one of the benefits of this approach is that it provides an objective measure of evidence independent of categorical thresholds for significance, they cited rough interpretive guidelines provided by Royall (1997): per his recommendations, a ratio of ± 3 bits may be considered "fairly strong evidence," whereas a ratio of ± 5 bits may be considered "strong evidence." (pp. 141–142)

In the current experiment, response accuracy data were evaluated using mixed-logistic regression models (Jaeger, 2008), while response time data were analyzed using linear-mixed-effect models (Baayen et al., 2008). Unless noted, models were run with the maximal crossed random effects structure for subjects and items justified by the design (Barr et al., 2013).

Analyses were conducted using R statistical software (R Development Core Team, 2008) via RStudio Version 0.98.1028, and version 1.1-7 of the lme4 package (Bates, 2005). For determining *p* values, degrees of freedom were estimated via Satterthwaite approximation via the lmerTest package version 2.0-20 (Kuznetsova et al., 2014), and used a .05 criterion for determining significance. Figures were generated with the ggplot2 package (Wickham, 2014).

## 8.3. Results

Practice trials were removed prior to analyses. PWA15 was unable to complete this task (0% accuracy on both the Low EA-Food and High EA-Animal conditions), and their data was removed prior to analyses.

### *8.3.1. Accuracy*

Mean accuracy rates by group, EA demand, and semantic category are presented in figure 8.1. The crucial dependent variable of interest was accuracy on the infrequent food category in the Low vs. High EA demand conditions. Therefore, mixed-effect logistic regressions were used to test for main effects of EA demand and group on accuracy of responses to the food category, and also for a 2-way interaction between group and EA demand on this dependent variable (table 8.1). Given the unbalanced design (23 MCs and 19 PWA in the current analyses), models used simple effects coding instead of contrast coding to avoid systematic bias (Davis, 2010), and therefore main effects were tested in separate models without the inclusion of interaction effects (Baayen et al., 2008). Model results revealed robust main effects of both EA demand and group; for EA demand, performance in the hard EA condition was worse than the easy EA condition in both groups, and for group, PWA performed worse than MCs in both the easy and hard EA demand conditions. In addition, these main effects were qualified by a marginally significant interaction between group and EA demand ($p$ = .09), with PWA performing marginally worse as EA demands increased. However, the log-base-2 likelihood ratio for this interaction was only 1.58, meaning that given the observed data, the chances of a true interaction are only about 3 times more likely than a null effect.

**Figure 8.1. Experiment 1: Semantic SART Accuracy by Group and EA Demand.**

Note: for the infrequent category (foods), a “correct” trial required a key press in the Low EA condition but a withheld response in the High EA condition. Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).

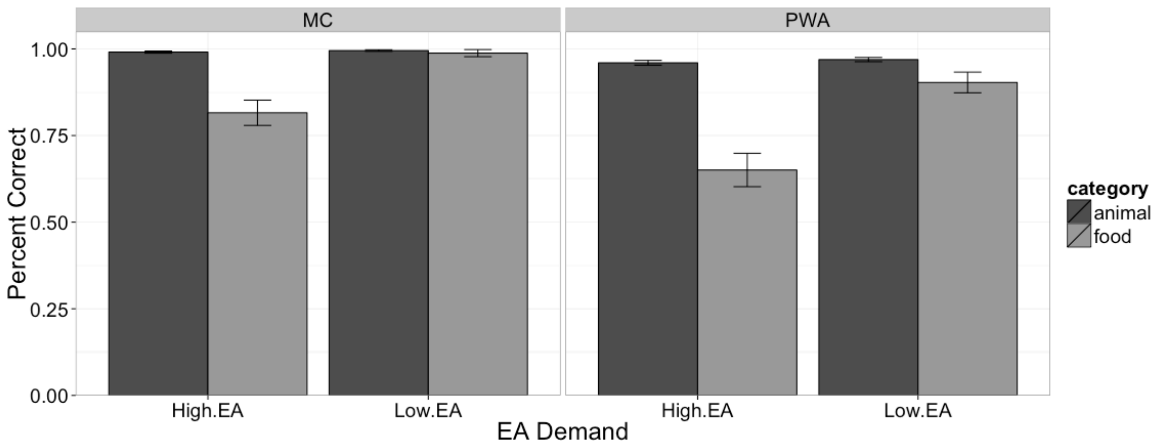



**Table 8.1. Experiment 1: Semantic SART. Fixed effect estimates from logistic mixed-effect models of response accuracy on group and EA demand.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **8.1.1. Main effects of group** | | | | |
| (Intercept) | 1.77 | 0.38 | 4.72 | <.001 |
| Group | -0.95 | 0.33 | -2.85 | <.001 |
| **8.1.2. Main effects of EA demand** | | | | |
| (Intercept) | 1.34 | 0.00 | 1997.00 | <.001 |
| EA Demand | 4.18 | 0.00 | 6234.00 | <.001 |
| **8.1.3. Group x EA demand.** | | | | |
| (Intercept) | 1.77 | 0.37 | 4.77 | <.001 |
| EA Demand | 4.50 | 0.98 | 4.60 | <.001 |
| Group | -0.95 | 0.33 | -2.84 | <.001 |
| EA Demand: Group | -1.61 | 0.95 | -1.70 | 0.09 |
| *Bits of evidence: 1.59* | | | | |

Note: Reference value for Group= MC, reference value for EA Demand = Hard EA.

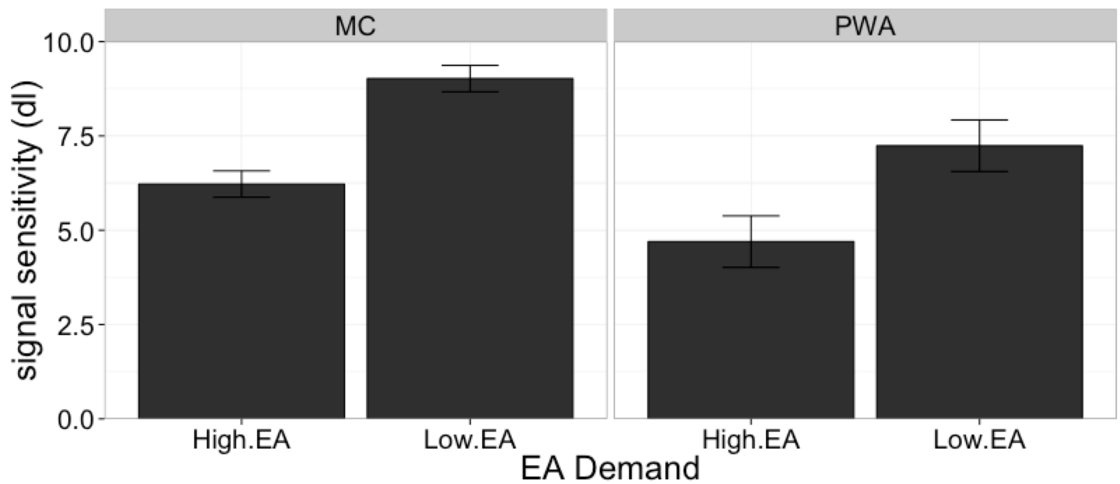
*8.3.2. Accuracy: Signal Sensitivity*

In addition to the analysis of response accuracy for the infrequent food category in the previous section, an overall signal detection sensitivity score calculated based on the miss and false alarm rates of both food and animal categories ($d_{L;}$ Snodgrass & Corwin, 1988), per the methods of McVay and Kane (2012). This measure, $d_L$, was calculated as follows for each participant and EA condition: ln{[H(1 – FA)]/[(1 – H)FA]}, where H= the proportion of key presses for food words in the Low EA condition and animals in the High EA condition ("hits"), and FA= the proportion of key presses for animal words in the Low EA condition and food in the High EA condition ("false alarms"). Mean $d_L$ and 95% confidence intervals are presented in figure 8.2.

In contrast to analyses of raw accuracy, effects on $d_L$ employed a 2x2 repeated measures ANOVA looking at the interaction between group and EA demand, with EA demand as a within-subject factor and group as a between-subject factor. Results were consistent with mixed-effect logistic regression analyses of response accuracy in terms of main effects for group and EA demand: performance in the hard EA condition was worse than the easy EA condition across groups $F(1, 40) = 119$, $p < .001$, and PWA performed worse than MCs across EA demand conditions $F(1, 40) = 11.8$, $p = .001$. However, there was no evidence of an interaction in this analysis, $F(1, 40) = .267$, $p = 0.61$.

**Figure 8.2. Experiment 1: Semantic SART. Signal sensitivity ($d_L$) by Group and EA Demand.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).




*8.3.3. Response times*

Visual inspection of raw response times via quantile-quantile plots for each subject revealed a small number of extreme outliers and a general rightward skew of the response distributions. Therefore, cutoffs were set with responses below 200 ms and above 2000 ms dropped prior to analysis (less than 0.3% of trials), and response times were log-transformed prior to analyses. Mean raw response times by group, EA demand, and semantic category are presented in figure 8.3.

Given the fact that EA demand was manipulated by switching "go" and "no go" for the frequent and infrequent semantic categories, comparison of response times between levels of EA demand was not considered informative (McVay and Kane, 2012). Therefore, mixed-effect linear regressions were used to test for main effects of group on infrequent food category response times, separately by EA demand (table 8.2). These models revealed robust main effects of group, with PWA taking longer to respond in both EA demand conditions.

**Figure 8.3. Experiment 1: Semantic SART. Response times in seconds by Group and EA Demand.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).

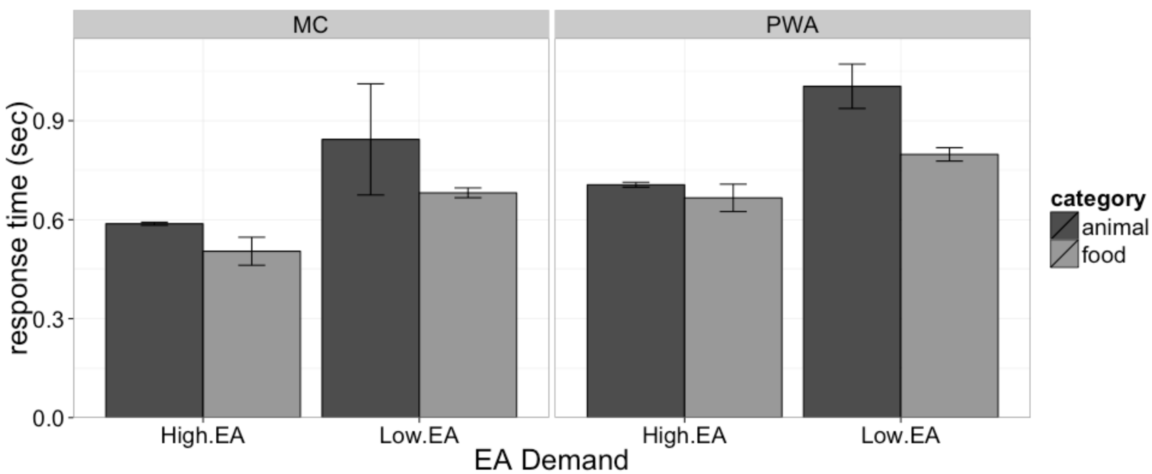



**Table 8.2. Experiment 1: Semantic SART. Fixed effect estimates from linear mixed-effect models of response times on group and EA demand.**

| | Estimate | Std. Error | Est. df | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| **8.2.1. Main effects of group in easy EA condition** | | | | | |
| (Intercept) | -0.40 | 0.04 | 17.97 | -9.13 | <.001 |
| Group | 0.16 | 0.05 | 39.52 | 3.25 | <.001 |
| | | | | | |
| **8.2.2. Main effects of group in hard EA condition** | | | | | |
| (Intercept) | -0.73 | 0.06 | 17.63 | -11.77 | <.001 |
| Group | 0.24 | 0.07 | 53.04 | 3.17 | <.001 |

Note: reference value for Group= MC.

## 8.4. Discussion

Although the response durations of each trial was doubled compared to previous designs (e.g., McVay and Kane, 2009, 2012; Robertson et al., 1997), this experiment was still sensitive to manipulations of EA demand in terms of response accuracy. In addition, with the exception of PWA15, all PWA participants were able to complete this version of the task; as a group, PWA did respond more slowly than MCs, but responses were well within the allotted response windows.

Overall, both types on accuracy analysis, signal sensitivity and response accuracy for the infrequent food category showed effects of group, with PWA performance worse than MCs in both the easy and hard EA demand conditions. However, these analyses differed in terms of evidence for an interaction between group and EA demand, with a marginally-significant interaction present only on the mixed-effect logistic regression analysis of response accuracy. This difference may be due to the fact that the signal sensitivity measure took into account responses for both food and animal categories, and animal category responses differed very little between groups due to ceiling effects. However, given the inconsistent and marginal effects, it is unlikely that these results reflect a true group interaction.

On its own, this pattern of results, in which PWA performed worse than controls regardless of EA demand, supports multiple interpretations regarding the locus of impairment: these PWA could possess a general semantic deficit affecting all types of semantic category judgment, and/or they could possess a sustained attention deficit. What is clear is that they do not have any additional executive attention difficulties inhibiting pre-potent motor responses in this task, above and beyond difficulties caused by existing lower-level semantic or sustained attention deficits.

From this single experiment it is not possible to distinguish between semantic impairment and general attention deficits at sources of poor performance. Experiment 2 was a direct methodological correlate of experiment 1, but employed a perceptual classification, and was included in the experimental battery to help make this distinction between sources of impaired performance.

# CHAPTER NINE

# Experiment 2: Perceptual Sustained Attention to Response

## 9.1. Methods and Procedure for Experiment 2

### *9.1.1. Materials and Design*

Experiment 2 used the same SART paradigm and design as experiment 1, with the only differences being the stimuli employed for the classification task. This experiment required a perceptual classification, following the methods of Smallwood et al. (2006) and McVay and Kane (2009), in which participants were asked to classify a series of visually presented letter strings (*O's* vs. *X's*) of varying lengths. This task was presented in two conditions, one with low executive attention demand (Low EA), and one with high executive attention demand (High EA).

In both conditions, *O's* were presented on 89% of trials and *X's* on 11% of trials. In the Low EA condition, a key press (the space bar) was required in response to the infrequent category (*X's*), making this essentially a test of sustained attention without any required prepotent response inhibition. In contrast, in the High EA condition, participants were asked to respond to the frequent category (*O's*) and withhold their response when presented with the infrequent category (*X's*). Stimuli were presented in black text on a white background on an LCD laptop monitor, and responses were recorded on an external USB keyboard.

Overall, Experiment 2 employed a 2x2x2 mixed factorial design, with perceptual category (*O's*, *X's*) and executive attention demand (high vs. Low EA) as within-subject factors, and group (PWA vs. matched control) as a between-subject factor.

### *9.1.2. Procedure*

A total of 550 stimuli were presented in this task, split evenly between Low EA and High EA conditions. In each EA condition, 225 stimuli were presented in five consecutive blocks without breaks in between them. Each block presented 40 trials of *O's* (stimuli varying in length from '*OO*' to '*OOOOOO*', with eight presentations of each length) and five trials of *X's* (stimuli varying in length from '*XX*' to '*XXXXXX*', with one presentation of each length). Presentation order was randomized within each block.

Participants were each presented with the Low EA condition blocks first, followed by the High EA condition blocks, and participants were given the option to take a short break between conditions. Although this design decision potentially conflates fatigue with executive attention demand, it also holds the effect of task order and practice constant across participants and ensures that the Hard EA condition was maximally demanding.

An initial version of experiment 2 was created alongside experiment 1 using the same presentation durations and piloted on the same set of 8 college-aged controls and 2 participants with aphasia (PWA1 and PWA2). In contrast to experiment 1, PWA1 and PWA2 were both able to complete this task at a basic level (for the infrequent *X's* category, PWA1 had an accuracy rate of 24% while PWA2 had a rate of 48%). However, given the need to modify presentation durations for experiment 1, durations in this task were also changed to keep both experiments as evenly matched as possible. Therefore, each stimulus was presented for 600 ms, followed by a 1900 ms pattern mask of 12 "*#'s*". A 10 ms inter-trial interval was also added in order to facilitate the loading and timing of images, resulting in a full 2500 ms between the onset of each new trial.

Each condition was preceded by a set of written instructions that were read to each participant, followed by two rounds of practice with a list of 15 stimuli (3 *X's*, 12 *O's*). To ensure equal task comprehension across participants, PWA were given the option to take two additional rounds of practice in the experiment if needed. If this second round of practice was requested, they were also given optional offline practice and additional instruction using index cards and an unplugged keyboard to ensure basic ability to make perceptual classifications of this type and retain the stimulus/response mappings in an untimed context. Although some PWA were noted to initially confuse the target *X's* and the pattern mask of *#'s*, all participants stopped responding to the pattern mask within the first 2 sets of practice, and were therefore deemed to be able to accurately discriminate them. All participants were asked to focus on both speed and accuracy in their responses.

As in experiment 1, in the Low EA condition, performance was interpreted as a measure of sustained attention given the demands placed on task maintenance in the relative absence of interference. In the High EA condition, it was interpreted as a measure of executive attention based on the combined requirements of maintaining task set while resolving interference generated by motor habituation.

## 9.2. Statistical Techniques

Analytical techniques followed the methods of experiment 1, including data cleaning procedures, statistical models, and selection of dependent variables.

## 9.3. Results

Analyses were conducted on the full set of 20 PWA and 23 MCs.

### *9.3.1. Accuracy*

Mean accuracy rates by group, EA demand, and perceptual category are presented in figure 9.1. The crucial dependent variable of interest was accuracy on the infrequent *X's* category in the Low vs. High EA demand conditions. Therefore, mixed-effect logistic regressions were used to test for main effects of EA demand and group on accuracy of responses to the food category, and also for a 2-way interaction between group and EA demand on this dependent variable (table 9.1). Model results revealed robust main effects of both EA demand and group; for EA demand, performance in the hard EA condition was worse than the easy EA condition in both groups, and for group, PWA performed worse than MCs in both the easy and hard EA demand conditions. There was no significant interaction between group and EA demand.

**Figure 9.1. Experiment 2: Perceptual SART Accuracy by Group and EA Demand.**

Note: for the infrequent category (*X's*), a "correct" response required a key press in the Low EA condition but required a withheld response in the High EA condition. Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).

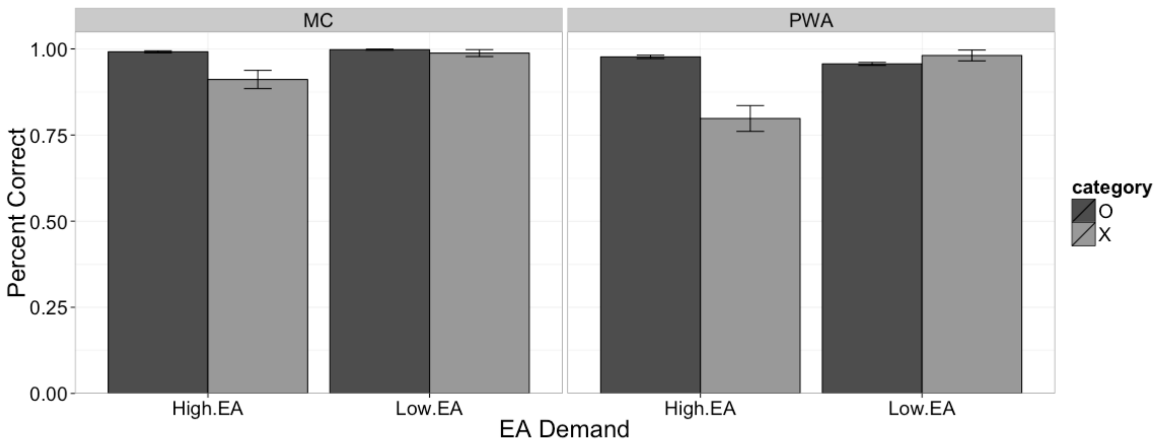



**Table 9.1. Experiment 2: Perceptual SART. Fixed effect estimates from logistic mixed-effect models of response accuracy on group and EA demand.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **9.1.1. Main effects of group** | | | | |
| (Intercept) | 2.23 | 0.22 | 10.27 | <.001 |
| EA | 4.19 | 1.78 | 2.36 | 0.02 |
| | | | | |
| **9.1.2. Main effects of EA demand** | | | | |
| (Intercept) | 3.31 | 0.00 | 2970.10 | <.001 |
| Group | -0.90 | 0.00 | -805.20 | <.001 |
| | | | | |
| **9.1.3. Group x EA demand.** | | | | |
| (Intercept) | 2.70 | 0.29 | 9.36 | <.001 |
| EA Demand | 4.01 | 1.76 | 2.28 | 0.022 |
| Group | -0.99 | 0.39 | -2.55 | 0.011 |
| EA Demand: Group | 0.16 | 1.11 | 0.15 | 0.882 |

Note: Reference value for Group= MC, reference value for EA Demand = Hard EA.

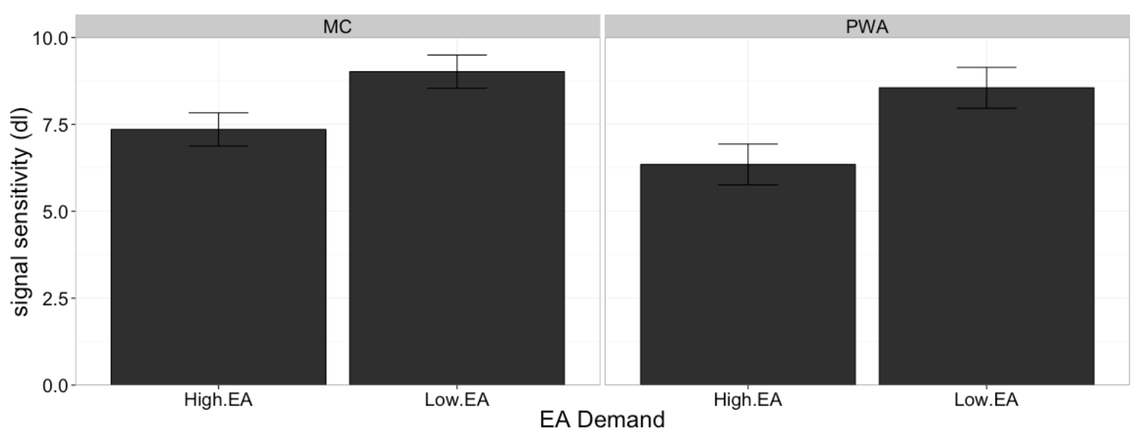
*9.3.2. Accuracy: Signal Sensitivity*

Signal sensitivity as measured by $d_L$ was calculated for each participant and EA demand condition. Mean $d_L$ and 95% confidence intervals by group are presented in figure 9.2, with ANOVA results in table 2.

As in the mixed-effect logistic regression analyses of response accuracy, there was a main effect of EA demand, such that performance in the hard EA condition was worse than the easy EA condition across groups $F(1, 42) = 56.73$, $p < .001$, but there was no main effect of group $F(1, 42) = 2.548$, $p = 0.12$. There was also no interaction between group and EA demand $F(1, 42) = 1.43$, $p = 0.29$.

**Figure 9.2. Experiment 2: Perceptual SART. Signal sensitivity ($d_L$) by Group and EA Demand.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).



*9.3.3. Response times*

As in experiment 1, cutoffs were set with responses below 200 ms and above 2000 ms dropped prior to analysis (less than 0.2% of trials), and response times were log-transformed prior to analyses. Mean raw response times rates by group, EA demand, and perceptual category are presented in figure 9.3.

Mixed-effect linear regressions were used to test for main effects of group on the infrequent *X's* category response times, separately by EA demand (table 9.2). These models revealed robust main effects of group, with PWA taking longer to respond in both EA demand conditions.

**Figure 9.3. Experiment 2: Perceptual SART. Response times in seconds by Group and EA Demand.**

Note: for the infrequent category (*X's*), a "correct" trial required a key press in the Low EA condition but a withheld response in the High EA condition. Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).

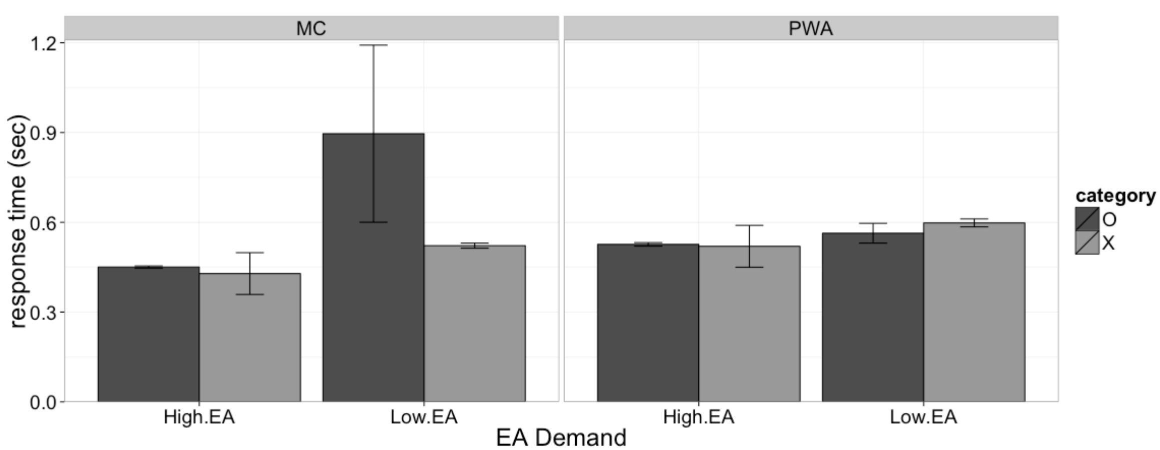


**Table 9.2. Experiment 2: Perceptual SART. Fixed effect estimates from linear mixed-effect models of response times on group and EA demand.**

| | Estimate | Std. Error | Est. df | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| **9.2.1. Main effects of group in easy EA condition** | | | | | |
| (Intercept) | -0.66 | 0.03 | 43.84 | -21.68 | <.001 |
| Group | 0.12 | 0.04 | 42.01 | 2.85 | 0.01 |
| **9.2.2. Main effects of group in hard EA condition** | | | | | |
| (Intercept) | -0.92 | 0.09 | 55.34 | -10.33 | <.001 |
| Group | 0.16 | 0.12 | 42.46 | 1.36 | 0.18 |

Reference value for Group= MC.

### 9.4. Discussion

As in experiment 1, doubling of response durations for each trial did not eliminate effects of EA demand on response accuracy. Overall, both types of accuracy analysis (signal sensitivity and response accuracy for the infrequent *X's* category) showed effects of EA demand, with both PWA and MCs performing worse in High EA demand condition. Neither analysis showed evidence for an interaction between group and EA demand. Group differences were only found in the mixed-effect logistic regression analysis of accuracy and not on analysis of signal sensitivity. This difference is likely due to the fact that signal sensitivity incorporated responses for the frequent O's category as well, and PWA were as close to ceiling as controls on this condition.

As in experiment one, PWA performed worse than controls on accuracy for the infrequent category in both the easy and hard EA conditions. This finding rules out semantic deficits being the single causative factor for difficulty in experiment 1, as the judgment in the current task was based on a simple perceptual letter classification.

Although PWA performed more slowly on both experiments, simple motor slowing could not account for worse performance in accuracy, as responses were all well within the given time windows. Given the current pattern of results, a sustained attention deficit is the most likely, although other domain-general sources of difficulty cannot be ruled out. Finally, it is clear from these results that as a group, PWA do not have executive attention deficits in actively inhibiting pre-potent motor responses in these tasks.

Please refer to Chapter 12 for direct statistical comparison of results from experiment 1 and experiment 2, as well as general discussion regarding the overall implications of PWA performance on these executive attention measures.

# CHAPTER TEN

## Experiment 3: Word-Picture Interference

## 10.1. Methods and Procedure for Experiment 3

### *10.1.1. Materials and Design*

In experiment 3, participants were required to classify written words (animal vs. non-animal) visually embedded in the center of a congruent, neutral, or interfering picture (animal, non-animal, or shape), following the methods of Lim (2011). Please refer to figure 10.1 for examples. Lim describe his stimuli generation as follows:

> The experimental stimuli for the PWI task were created by placing each of these words within a background line-drawn picture that was of high typicality and discriminability. To create the stimuli (animals and non-animal), line drawings as picture stimuli were chosen from a previous PWI study (Dunbar, 1986)[6], in which all stimuli were taken from the Snodgrass and Vanderwart's (1980) normed stimuli. […]Background line-drawn pictures were taken from the Peabody Picture Vocabulary Test (PPVT; Dunn & Dunn, 1997) and Pyramids and Palm Trees test (PPT; Howard & Patterson, 1992). (p. 43)

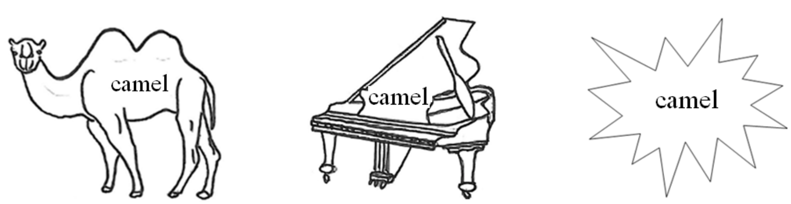
Lim manipulated hard vs. easy EA demand by presenting condition blocks with 19% and 73% proportion of incongruent trials, respectively. The rationale for this

[6]While cited, this study was not referenced and could not be found by the author.

contrast was that maintaining the full task set (i.e., "classify the word and ignore the picture") was much easier in the 73% incongruent compared to 19% incongruent condition due to constant reinforcement from interfering pictures, which minimized interference effects. The current experiment used this same basic design with the following changes: the high and easy EA proportion manipulations were shifted to 76% and 24% proportion of incongruent trials to match those from experiment one from Kane and Engle (2003), and the number of trials was increased from 240 to 800 to increase statistical power. In addition, only 8 of the 10 stimuli from Lim (2011) were used. This was in order to eliminate systematic differences in the number of times words and pictures appeared together in congruent vs. incongruent items, as this measure of executive attention is based on conflict adaption to the proportion-congruent effect, and item-specific proportion manipulations have been shown to modulate this effect (Schmidt, 2013).

**Figure 10.1. Three example stimuli from experiment 3 taken from Lim (2011).**

Presented left to right are examples of congruent, incongruent, and neutral stimuli for a trial requiring an "animal" classification based on the category of the target word.




Overall, Experiment 3 employed a 3x2x2 mixed factorial design, with item congruency (congruent, incongruent, or neutral pictures paired with a target word) and executive attention demand (hard vs. easy EA) as within-subject factors, and group

(PWA vs. MC) as a between-subject factor. Task maintenance ability was measured based on differences in interference effects between the easy and hard EA demand conditions, while conflict resolution ability was measured by comparing interference effects in the easy EA demand condition.

### *10.1.2. Procedure*

A total of 800 trials were presented in this task, split evenly between easy EA and hard EA conditions. In each EA condition, 400 trials were presented in blocks of 100, with a break offered between each block. Participants were each presented with the hard EA condition blocks first, followed by the easy EA condition blocks. Presentation order was randomized within each block.

In the hard EA condition, each block contained the same list of 24 incongruent stimuli, 24 neutral stimuli, and 52 congruent stimuli. The frequency of target words and their corresponding pictures was balanced across condition, with all 8 targets words and corresponding pictures occurring 3 times each in incongruent trials, and 6 or 7 times each in congruent trials. All 8 targets words occurred 3 times each in neutral trials along with a single geometric shape.

In the easy EA condition, each block contained the same list of 76 incongruent stimuli and 24 neutral stimuli. All 8 targets words and corresponding pictures occurred 9 or 10 times each in incongruent trials, and all 8 targets words occurred 3 times each in neutral trials.

Each trial consisted of a fixation cross appearing for 1000 ms and a 200 ms interval in which nothing was presented, followed by presentation of one of the stimuli, which remain on the screen until the participant made a response.

Prior to testing, PWA participants were assessed on their ability to accurate categorize each word and each picture separately in an untimed task. All PWA participants were able to able to classify all words and pictures with 100% accurately in this context.

Each condition was preceded by a set of written instructions that were read to each participant, which were as follows:

> In this task, you will see words presented inside pictures. The picture may match the word, or be different from the word. Your job is to decide whether each word is an animal or non-animal, while ignoring the picture on each trial.
>
> If the word is an ANIMAL, press the LEFT arrow. If the word is NOT an animal, press the RIGHT arrow. Please respond as quickly as and as accurately as you can. Any questions? Press the space bar to try some practice.

This was followed by a practice list of 12 stimuli that provided accuracy feedback on responses. To maximize equal task comprehension across participants, PWA were given the option to take an additional round of practice in the experiment if needed. If this second round of practice was requested, they were also given optional offline practice and additional instruction using printed example stimuli and an unplugged keyboard to ensure basic ability to make classifications of this type in a supported context. All participants were asked to focus on both speed and accuracy in their responses.

## 10.2. Statistical Techniques

Analytical techniques followed the methods of experiment 1, including data cleaning procedures and statistical models. Analyses focused on response accuracy and response times for measures of task maintenance and conflict resolution. In several instances, mixed-effect models with maximal random effects structures including random slopes for interaction terms failed to converge; in such cases, random effects structures were simplified in backwards-elimination fashion, and these models are noted in the relevant table.

## 10.3. Results

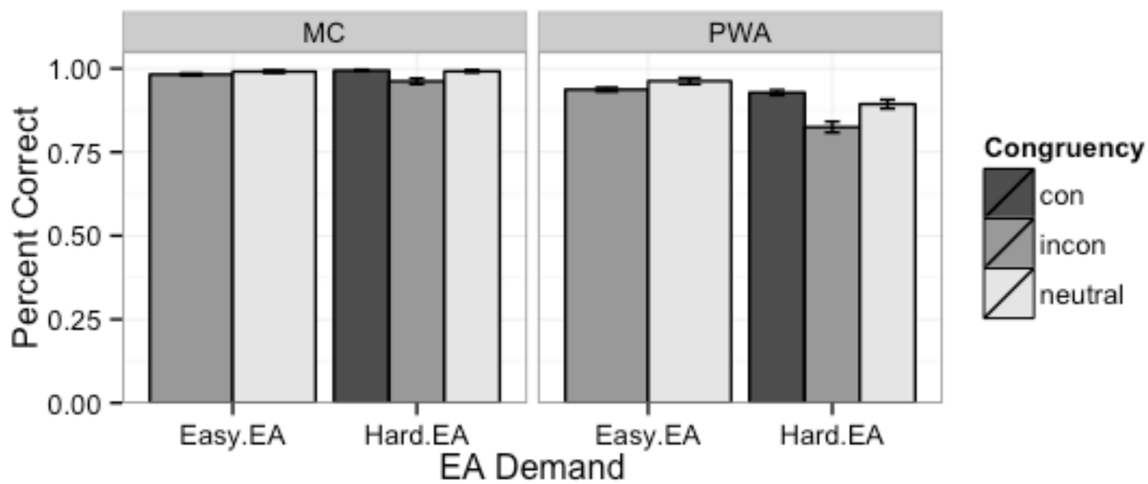
Analyses were conducted on the full set of 20 PWA and 23 MCs.

### *10.3.1. Accuracy*

Mean accuracy rates by group, EA demand, and congruency are presented in figure 10.2. For task maintenance, the crucial accuracy measure of interest was group differences in interference effects (incongruent vs. neutral trials) in the easy EA vs. hard EA conditions, while for conflict resolution it was group difference in interference effects in the easy EA condition. Therefore, a mixed-effect logistic regression was used to test the 3-way interaction between fixed effects of group, EA demand, and congruency (excluding congruent trials from the hard EA condition), predicting response accuracy (table 10.1; model 10.1.1).

**Figure 10.2. Experiment 3: Word-Picture Interference. Accuracy by group, EA demand, and congruency.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008). Easy EA condition presented trials blocks with 76% incongruent stimuli, while hard EA condition presented trial bocks with 24% incongruent stimuli.




Model results revealed a significant 3-way interaction ($p = 0.038$). This was interpreted by looking independently at a series of nested models testing each of the constituent 2-way interactions: the interaction between EA demand and congruency, separately by group, the interaction between group and congruency, separately by EA demand, and the interaction between group and EA demand, separately by congruency (table 10.1). Across the models, there were consistent significant effects of group and congruency ($p$s $< 0.05$), with PWA performing with lower accuracy than MCs, and incongruent trials associated with lower accuracy than neutral trials.

**Table 10.1 Experiment 3: Word-Picture Interference, primary analyses of response accuracy. Fixed effect estimates from logistic mixed-effect models of response accuracy on group, EA demand, and congruency.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **10.1.1 Group x EA demand x congruency** | | | | |
| (Intercept) | 5.52 | 0.41 | 13.41 | <0.001 |
| Congruency | -0.93 | 0.34 | -2.72 | 0.007 |
| EA Demand | 0.13 | 0.39 | 0.33 | 0.739 |
| Group | -0.95 | 0.47 | -2.02 | 0.044 |
| Congruency: EA Demand | -0.91 | 0.35 | -2.64 | 0.008 |
| Congruency: Group | 0.06 | 0.28 | 0.23 | 0.816 |
| EA Demand: Group | -1.27 | 0.48 | -2.62 | 0.009 |
| Congruency: EA Demand: Group | 0.81 | 0.39 | 2.07 | 0.038 |
| *Bits of Evidence for interaction: 2.9* | | | | |
| *AIC: 6911* | | | | |
| **10.1.2 Group x Congruency in Easy EA Condition.** | | | | |
| (Intercept) | 5.51 | 0.43 | 12.67 | <0.001 |
| Congruency | -0.85 | 0.37 | -2.27 | 0.023 |
| Group | -1.05 | 0.50 | -2.12 | 0.034 |
| Congruency: Group | 0.13 | 0.33 | 0.39 | 0.700 |
| **10.1.3 Group x Congruency in Hard EA Condition.** | | | | |
| (Intercept) | 6.10 | 0.58 | 10.54 | <0.001 |
| Congruency | -2.13 | 0.53 | -4.01 | <0.001 |
| Group | -2.06 | 0.61 | -3.37 | 0.001 |
| Congruency: Group | 0.61 | 0.41 | 1.51 | 0.130 |
| **10.1.4 Congruency x EA Demand in MC Group.** | | | | |
| (Intercept) | 5.21 | 0.34 | 15.34 | <0.001 |
| Congruency | -0.71 | 0.30 | -2.38 | 0.017 |
| EA Demand | 0.03 | 0.34 | 0.08 | 0.932 |
| Congruency: EA Demand | -0.90 | 0.35 | -2.59 | 0.010 |

| | | | | |
|---|---|---|---|---|
| **10.1.5 Congruency x EA Demand in PWA Group.** | | | | |
| (Intercept) | 4.65 | 0.44 | 10.49 | <0.001 |
| Congruency | -0.91 | 0.31 | -2.98 | 0.003 |
| EA Demand | -1.10 | 0.36 | -3.09 | 0.002 |
| Congruency: EA Demand | -0.10 | 0.19 | -0.55 | 0.584 |
| **10.1.6 Group x Congruency interaction for Neutral trials.** | | | | |
| (Intercept) | 5.68 | 0.56 | 10.20 | <0.001 |
| EA Demand | 0.11 | 0.30 | 0.37 | 0.714 |
| Group | -0.71 | 0.57 | -1.23 | 0.218 |
| EA Demand: Group | -1.52 | 0.34 | -4.47 | <0.001 |
| **10.1.7 Group x Congruency interaction for Incongruent trials.** | | | | |
| (Intercept) | 4.60 | 0.30 | 15.33 | <0.001 |
| EA Demand | -0.74 | 0.26 | -2.79 | 0.005 |
| Group | -0.94 | 0.41 | -2.29 | 0.022 |
| EA Demand: Group | -0.57 | 0.35 | -1.64 | 0.102 |

Note: Initial version of models 10.1.1 and 10.1.6 obtained convergence warnings and models with simplified random effects structures are presented. Reference value for Group= “MC”, reference value for EA Demand = “easy EA”, reference value for Congruency = “Neutral”.

Inspection of the nested models determined that the 3-way interaction was due to two sets of effects: first, group differences in the interaction between congruency and EA demand (models 10.1.4 and 10.1.5), and second, differences in the interaction effect between group and EA demand based on congruency type (models 10.1.6 and 10.1.7). In regards to the first, MCs showed an interaction between EA demand and congruency, with larger interference effects (incongruent vs. neutral trials) in the hard EA compared to easy EA demand condition ($p$ = 0.01), but there was no such interaction for the PWA group ($p = 0.58$). In regards to the second, there was a group x EA demand interaction on neutral trials, with PWA performing disproportionately worse in the hard EA condition ($p < 0.001$), but only a trend for this interaction on incongruent trials ($p = 0.10$). In sum, PWA did not demonstrate task maintenance effects in these models or a task maintenance deficit as hypothesized, and instead showed impaired performance on neutral trials in the hard EA context. Given pattern of overall worse performance for PWA on the hard condition, a 2-way interaction model crossing group x EA demand collapsing across congruency type was run as a secondary analysis (model 10.2.1), which found a significant interaction ($p = 0.043$), with PWA performing disproportionately worse than MCs in the hard EA condition overall.

One possible explanation for these results may be semantic processing ability: if general semantic processing ability had a effect on task performance for PWA, it might have shown up as overall worse performance in hard task blocks, and in addition, large effects of this type may have obscured any additional specific deficits in task maintenance. If so, performance on the Cactus and Camel Test (CCT), an independent measure of semantic processing ability, might moderate the interaction between congruency and EA demand in this group, with more typical task maintenance effects occurring in PWA with better CCT scores. A model looking at the 3-way interaction between congruency, EA demand, and centered CCT performance score was run to test this hypothesis (model 10.2.2). Although this model showed a significant effect of CCT performance on accuracy ($p < 0.01$), the three-way interaction was not significant ($p = 0.76$).

Finally, the presence of a conflict resolution deficit in PWA was tested for specifically by looking at the interaction of group and congruency in the easy EA demand condition, which was not significant ($p$ = 0.7; model 10.1.2).

**Table 10.2 Experiment 3: Word-Picture Interference, secondary analyses of response accuracy. Fixed effect estimates from logistic mixed-effect models of response accuracy on group, EA demand, and congruency.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **10.2.1 Group x EA demand, collapsing across congruency types.** | | | | |
| (Intercept) | 5.12 | 0.33 | 15.59 | <0.001 |
| EA Demand | -0.44 | 0.26 | -1.68 | 0.093 |
| Group | -0.89 | 0.41 | -2.16 | 0.031 |
| EA Demand: Group | -0.78 | 0.35 | -2.21 | 0.027 |
| (Intercept) | 4.40 | 0.38 | 11.58 | <0.001 |
| Congruency | -0.64 | 0.31 | -2.02 | 0.043 |
| EA Demand | -0.97 | 0.36 | -2.73 | 0.006 |
| **10.2.2 Congruency x EA Demand x CCT scores in PWA Group.** | | | | |
| CCT performance | 0.11 | 0.04 | 2.88 | 0.004 |
| Congruency: EA Demand | -0.21 | 0.20 | -1.01 | 0.312 |
| Congruency: CCT performance | 0.04 | 0.01 | 2.91 | 0.004 |
| EA Demand: CCT performance | 0.00 | 0.05 | 0.04 | 0.970 |
| Congruency: EA Demand: CCT performance | 0.01 | 0.02 | 0.31 | 0.755 |

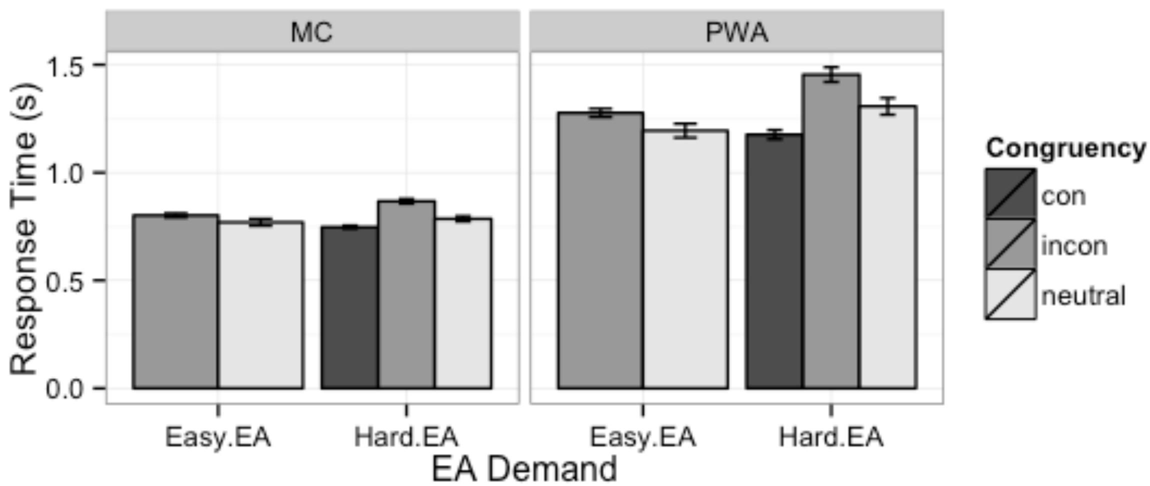
Note: Catus and Camel Test (CCT) scores centered prior to analysis. Reference value for Group= “MC”, reference value for EA Demand = “easy EA”, reference value for Congruency = “Neutral”.

*10.3.2. Response times*

Visual inspection of raw response times via quantile-quantile plots by subject revealed a small number of extreme outliers and a general rightward skew of the response distributions. Therefore, cutoffs were set with responses below 200 ms and above 8000 ms dropped prior to analysis (less than 0.2% of trials), and response times were log-transformed prior to analyses. Mean raw response times rates by group, EA demand, and semantic category are presented in figure 10.3.

**Figure 10.3. Experiment 3: Word-Picture Interference. Response time (s) by group, EA demand, and congruency.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008). Easy EA condition presented trials blocks with 76% incongruent stimuli, while hard EA condition presented trial bocks with 24% incongruent stimuli.




Log-transformed response times were analyzed using the same approach as for the accuracy data, except that linear mixed-effect regressions were used. The primary model tested for the presence of a 3-way interaction between the fixed effects of group, EA demand, and congruency (neutral vs. incongruent trials), followed by the same series of nested 2-way interaction models to investigate lower-order model effects (table 10.3).

In contrast to accuracy results, the 3-way interaction for response times was not significant ($p$ = 0.69; model 10.3.1). Investigation of the nested models determined that

that PWA and MC groups both showed a robust task maintenance effect between EA demand and congruency (*p*s < 0.001). This indicates that while PWA were sensitive to EA demands on response times, they did not demonstrate a task maintenance deficit. The secondary analysis looking at the interaction of group and congruency in the easy EA demand condition was also not significant ($p = 0.27$, model 10.3.2), indicating that the PWA group did not demonstrate a conflict resolution deficit on response time in this experiment. Across these models, there were also consistent significant effects of group and congruency (*p*s < 0.02), with PWA taking longer to respond than MCs, and incongruent trials associated with longer response times than neutral trials.

**Table 10.3. Experiment 3: Word-Picture Interference. Fixed effect estimates from linear mixed-effect models of response time on group, EA demand, and congruency. Group x EA demand x Congruency interaction.**

| | Estimate | Std. Error | Est. df | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| **10.3.1 Group x EA demand x congruency** | | | | | |
| (Intercept) | -0.32 | 0.04 | 44.44 | -7.49 | <0.001 |
| Congruency | 0.04 | 0.01 | 63.30 | 3.90 | <0.001 |
| EA Demand | 0.04 | 0.03 | 46.54 | 1.31 | 0.198 |
| Group | 0.39 | 0.06 | 42.46 | 6.32 | <0.001 |
| Congruency: EA Demand | 0.06 | 0.01 | 25300.67 | 5.47 | <0.001 |
| Congruency: Group | 0.02 | 0.01 | 25295.20 | 2.10 | 0.036 |
| EA Demand: Group | 0.03 | 0.04 | 46.55 | 0.79 | 0.432 |
| Congruency: EA Demand: Group | 0.01 | 0.02 | 25295.20 | 0.39 | 0.699 |
| *Bits of Evidence for interaction: -2.67* | | | | | |
| *AIC: 11252* | | | | | |
| | | | | | |
| **10.3.2 Group x Congruency in Easy EA Condition.** | | | | | |
| (Intercept) | -0.32 | 0.04 | 43.89 | -7.91 | <0.001 |
| Congruency | 0.04 | 0.02 | 57.30 | 2.51 | 0.015 |
| Group | 0.39 | 0.06 | 40.99 | 6.72 | <0.001 |
| Congruency: Group | 0.02 | 0.02 | 40.97 | 1.11 | 0.272 |

| | | | | | |
|---|---|---|---|---|---|
| **10.3.3 Group x Congruency in Hard EA Condition.** | | | | | |
| (Intercept) | -0.28 | 0.04 | 42.13 | -6.92 | <0.001 |
| Congruency | 0.10 | 0.02 | 44.66 | 5.85 | <0.001 |
| Group | 0.42 | 0.06 | 41.00 | 7.16 | <0.001 |
| Congruency: Group | 0.03 | 0.02 | 40.96 | 1.17 | 0.247 |
| **10.3.4 Congruency x EA Demand in MC Group.** | | | | | |
| (Intercept) | -0.32 | 0.03 | 25.69 | -9.17 | <0.001 |
| Congruency | 0.04 | 0.01 | 35.64 | 3.55 | 0.001 |
| EA Demand | 0.04 | 0.03 | 24.43 | 1.49 | 0.149 |
| Congruency: EA Demand | 0.06 | 0.01 | 13537.10 | 6.85 | <0.001 |
| **10.3.5 Congruency x EA Demand in PWA Group.** | | | | | |
| (Intercept) | 0.07 | 0.05 | 20.23 | 1.32 | 0.202 |
| Congruency | 0.06 | 0.01 | 48.71 | 5.30 | <0.001 |
| EA Demand | 0.07 | 0.03 | 21.90 | 2.04 | 0.053 |
| Congruency: EA Demand | 0.07 | 0.01 | 11742.42 | 4.74 | <0.001 |
| **10.3.6 Group x Congruency interaction for Neutral trials.** | | | | | |
| (Intercept) | -0.32 | 0.04 | 42.56 | -7.97 | <0.001 |
| EA Demand | 0.04 | 0.02 | 40.97 | 1.63 | 0.111 |
| Group | 0.39 | 0.06 | 40.99 | 6.72 | <0.001 |
| EA Demand: Group | 0.03 | 0.03 | 40.98 | 0.99 | 0.329 |
| **10.3.7 Group x Congruency interaction for Incongruent trials.** | | | | | |
| (Intercept) | -0.28 | 0.04 | 41.67 | -6.45 | <0.001 |
| EA Demand | 0.10 | 0.03 | 40.97 | 3.04 | 0.004 |
| Group | 0.41 | 0.06 | 41.00 | 6.56 | <0.001 |
| EA Demand: Group | 0.04 | 0.05 | 40.97 | 0.82 | 0.415 |

Note: Initial version of model 10.3.1 obtained a convergence warning, and a model with simplified random effects structure is presented. Reference value for Group= "MC", reference value for EA Demand = "easy EA", reference value for Congruency = "Neutral".

## 10.4. Discussion

Experiment 3 manipulated the proportion of incongruent trials in a word-picture interference task to investigate the executive attention abilities of PWA in the semantic domain. The PWA group demonstrated the expected effects of congruency proportion manipulation based on interactions between EA demand and congruency: blocks with increased proportion of incongruent trials were associated with decreased interference effects on both response times and accuracy.

The PWA group did not demonstrate the hypothesized task maintenance or conflict resolution deficits. They performed worse than controls on this task overall, with lower accuracy rates and longer response times across conditions. They demonstrated expected effects of congruency proportion manipulation in response times, but not on accuracy. Instead, they showed disproportionately worse performance than MCs on neutral trials in hard EA condition compared to the easy EA condition. PWA also showed disproportionately worse performance than MCs in the hard EA compared to easy EA condition when collapsing across trial congruency types.

The above results were not predicted. They are not consistent with task maintenance or conflict resolution deficits as hypothesized in the context of the current experiment, which only predict specific differences in interference effects based on proportion congruency manipulations. These general performance decrements in the hard EA condition were not due to more general semantic processing impairments as measured by the CCT, as this measure did not moderate the congruency by EA demand interaction effects for this group. Conversely, this lack of moderating effect can also be interpreted as evidence against the semantic control account of Lambon Ralph and colleagues, in which semantic deficits in post-stroke aphasia are attributed to deficits in “executive processes that help to direct and control semantic activation in a task-appropriate fashion" (Jefferies and Lambon Ralph, 2006, p. 2132).

The presence of PWA impairments not specifically tied to interference effects invites reinvestigation of the underlying executive attention construct. In the original model, Engle and Kane (2004) conceptualized task maintenance as the ability to hold relevant task goals active in working memory in such a way that they are able to exert proactive control and reduce interference from task-irrelevant aspects of incongruent stimuli. However, in order to move from an actively maintained goal to the point of reduced interference, many additional operations may be required within tasks like the current experiment. One such mechanism, which has been suggested as an alternative to attention-based accounts of task maintenance effects, is that of stimulus-response mapping (e.g., Oberauer et al., 2007). Since the hard EA condition had a greater variability stimuli types given the inclusion of congruent trials, it is possible that PWA had difficulty learning the appropriate stimulus-response bindings in such contexts (i.e., determining which elements of the current stimulus necessitate a specific response), independent of any difficulty resolving interference. If so, stimulus-response mapping difficulty could affect performance across congruency conditions and at least partially account for the current findings.

On a final note, it should be pointed out that the lack of PWA task maintenance deficits was not due to any insensitivity to the proportion congruency effect, as PWA were as equally sensitive as MCs to these effects on response times.

# CHAPTER ELEVEN

## Experiment 4: Nonverbal Spatial Stroop

### 11.1. Methods and Procedure for Experiment 4

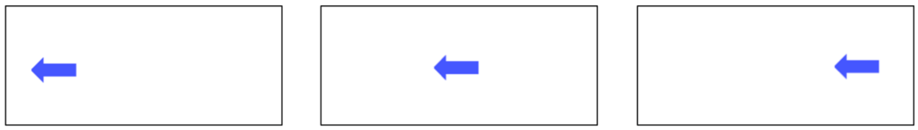
#### *11.1.1. Materials and Design*

In experiment 4, participants were required to respond to pictured arrows pointing to the left or right appearing in congruent, neutral, or incongruent screen locations, following the basic methodology of Hamilton & Martin (2005). Apart from the classification task and stimuli, all other aspects of this task were matched to experiment 4. Therefore, this task was considered an executive attention measure based on the proportion congruency effect in the visuospatial domain.

As stated, arrows were presented in the middle (neutral) and left and right (congruent/incongruent) sides of the screen (please refer to figure 11.1 for examples). The first block of trials presented incongruent trials (left-pointing arrows on the right side of the screen, right-pointing arrows on the left side of the screen) 24% of the time, while the second block of trials presented incongruent trials 76% of the time.

**Figure 11.1. Three example stimuli from experiment 4, taken from Hamilton and Martin (2005).**

Presented left to right are examples of congruent, neutral, and incongruent stimuli for a trial requiring a "left" response base on the direction of the depicted arrow.



Overall, Experiment 4 employed a 3x2x2 mixed factorial design, with item congruency (with screen location congruent, incongruent, or neutral compared to direction of arrow) and executive attention demand (hard vs. easy EA) as within-subject factors, and group (PWA vs. matched control) as a between-subject factor. Task maintenance ability was measured based on differences in interference effects between the easy and hard EA demand conditions, while conflict resolution ability was measured by comparing interference effects in the easy EA demand condition.

*11.1.2. Procedure*

A total of 800 trials were presented in this task, split evenly between easy EA and hard EA conditions. In each EA condition, 400 trials were presented in blocks of 100, with a break offered between each block. Participants were each presented with the hard EA condition blocks first, followed by the easy EA condition blocks. Presentation order was randomized within each block.

In the hard EA condition, each block contained 24 incongruent stimuli, 24 neutral stimuli, and 52 congruent stimuli. In the easy EA condition, each block contained 76 incongruent stimuli and 24 neutral stimuli. The proportion of left-pointing and right-pointing arrows was counterbalanced across conditions.

Each trial consisted of a fixation cross appearing for 1000 ms and a 200 ms interval in which nothing was presented, followed by presentation of one of the stimuli, which remain on the screen until the participant made a response.

Each condition was preceded by a set of written instructions that were read to each participant, which were as follows:

> In this task, you will press keys to indicate which direction an arrow is pointing. The arrows will be pointing to either the left of the right. If the arrow is pointing to the LEFT, press the "Left" key on the keyboard. If the arrow is pointing to the RIGHT, press the "Right" key on the keyboard. Any questions? Press the spacebar to begin practice.

This was followed by a practice list of 12 stimuli that provided accuracy feedback on responses. All participants were asked to focus on both speed and accuracy in their responses.

## 11.2. Statistical Techniques

Analytical techniques followed the methods of experiment 3, including data cleaning procedures and statistical models. Analyses focused on accuracy and response time for measures of task maintenance and conflict resolution.

## 11.3. Results

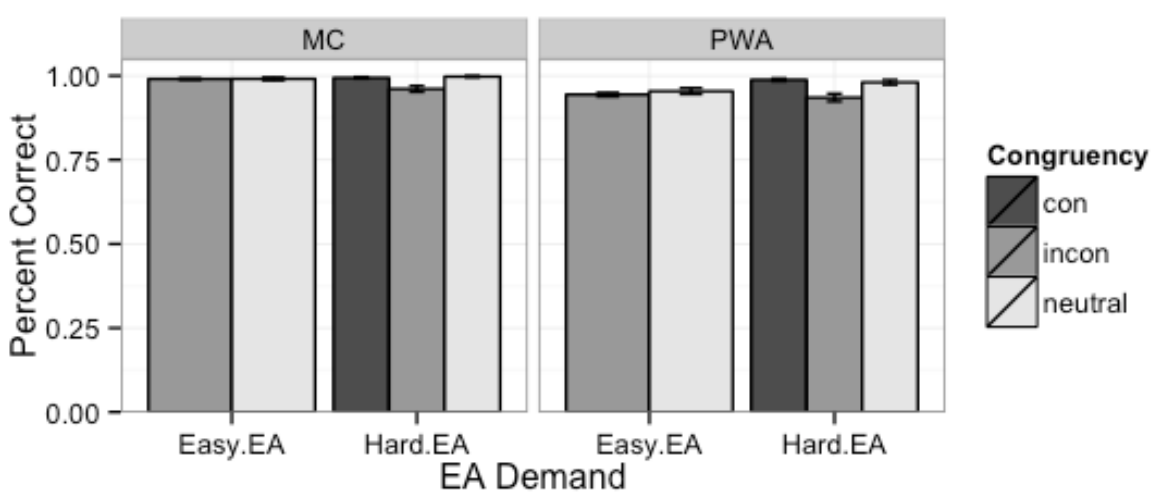
Analyses were conducted on the full set of 20 PWA and 23 MCs.

### *11.3.1. Accuracy*

Mean accuracy rates by group, EA demand, and congruency are presented in figure 11.2. For task maintenance, the crucial accuracy measure of interest was group differences in interference effects (incongruent vs. neutral trials) in the easy EA vs. hard EA conditions, while for conflict resolution it was group difference in interference effects in the easy EA condition. Therefore, a mixed-effect logistic regression was used to test the 3-way interaction between fixed effects of group, EA demand, and congruency (excluding congruent trials from the hard EA condition), predicting response accuracy (table 11.1, model 11.1.1).

**Figure 11.2. Experiment 4: Spatial Stroop. Accuracy by group, EA demand, and congruency.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008). Easy EA condition presented trials blocks with 76% incongruent stimuli, while hard EA condition presented trial bocks with 24% incongruent stimuli.



Model results revealed a significant 3-way interaction ($p = 0.001$). This was interpreted by looking independently at the nested models testing each of the constituent 2-way interactions: the interaction between EA demand and congruency, separately by group, the interaction between group and congruency, separately by EA demand, and the interaction between group and EA demand, separately by congruency (table 11.1). Across these models, there were consistent significant effects of group ($p$s $< 0.05$), with PWA performing with lower accuracy than MCs.

**Table 11.1 Experiment 4: Spatial Stroop, primary analyses of response accuracy. Fixed effect estimates from logistic mixed-effect models of response accuracy on group, EA demand, and congruency.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **11.1.1 Group x EA demand x congruency** | | | | |
| (Intercept) | 5.55 | 0.40 | 13.93 | <0.001 |
| Congruency | -0.04 | 0.25 | -0.15 | 0.882 |
| EA Demand | 1.12 | 0.54 | 2.08 | 0.037 |
| Group | -1.45 | 0.53 | -2.75 | 0.006 |
| Congruency: EA Demand | -2.90 | 0.51 | -5.65 | <0.001 |
| Congruency: Group | -0.27 | 0.29 | -0.92 | 0.357 |
| EA Demand: Group | -0.50 | 0.61 | -0.82 | 0.413 |
| Congruency: EA Demand: Group | 1.85 | 0.57 | 3.25 | 0.001 |
| *Bits of Evidence for interaction:* 13.88 | | | | |
| *AIC:* 5071 | | | | |
| **11.1.2 Group x Congruency in Easy EA Condition.** | | | | |
| (Intercept) | 5.81 | 0.46 | 12.53 | <0.001 |
| Congruency | -0.32 | 0.29 | -1.11 | 0.267 |
| Group | -1.43 | 0.60 | -2.39 | 0.017 |
| Congruency: Group | -0.33 | 0.30 | -1.07 | 0.285 |
| **11.1.3 Group x Congruency in Hard EA Condition.** | | | | |
| (Intercept) | 6.70 | 0.56 | 11.87 | <0.001 |
| Congruency | -2.99 | 0.51 | -5.89 | <0.001 |
| Group | -1.92 | 0.63 | -3.06 | 0.002 |
| Congruency: Group | 1.59 | 0.51 | 3.13 | 0.002 |
| **11.1.4 Congruency x EA Demand in MC Group.** | | | | |
| (Intercept) | 5.49 | 0.39 | 14.05 | <0.001 |
| Congruency | -0.04 | 0.25 | -0.15 | 0.883 |
| EA Demand | 1.07 | 0.54 | 1.99 | 0.046 |
| Congruency: EA Demand | -2.89 | 0.52 | -5.59 | <0.001 |
| **11.1.5 Congruency x EA Demand in PWA Group.** | | | | |
| (Intercept) | 4.10 | 0.37 | 11.05 | <0.001 |
| Congruency | -0.30 | 0.14 | -2.16 | 0.031 |
| EA Demand | 0.70 | 0.34 | 2.09 | 0.036 |
| Congruency: EA Demand | -1.06 | 0.24 | -4.42 | <0.001 |

| | | | | |
|---|---|---|---|---|
| **11.1.6 Group x Congruency interaction for Neutral trials.** | | | | |
| (Intercept) | 5.78 | 0.51 | 11.42 | <0.001 |
| EA Demand | 1.43 | 0.50 | 2.84 | 0.004 |
| Group | -1.63 | 0.61 | -2.65 | 0.008 |
| EA Demand: Group | -0.35 | 0.55 | -0.64 | 0.520 |
| **11.1.7 Group x Congruency interaction for Incongruent trials.** | | | | |
| (Intercept) | 5.45 | 0.35 | 15.64 | <0.001 |
| EA Demand | -1.75 | 0.28 | -6.19 | <0.001 |
| Group | -1.70 | 0.47 | -3.58 | <0.001 |
| EA Demand: Group | 1.38 | 0.36 | 3.85 | <0.001 |

Note: Initial version of models 11.1.1 and 11.1.6 obtained convergence warnings and models with simplified random effects structures are presented.

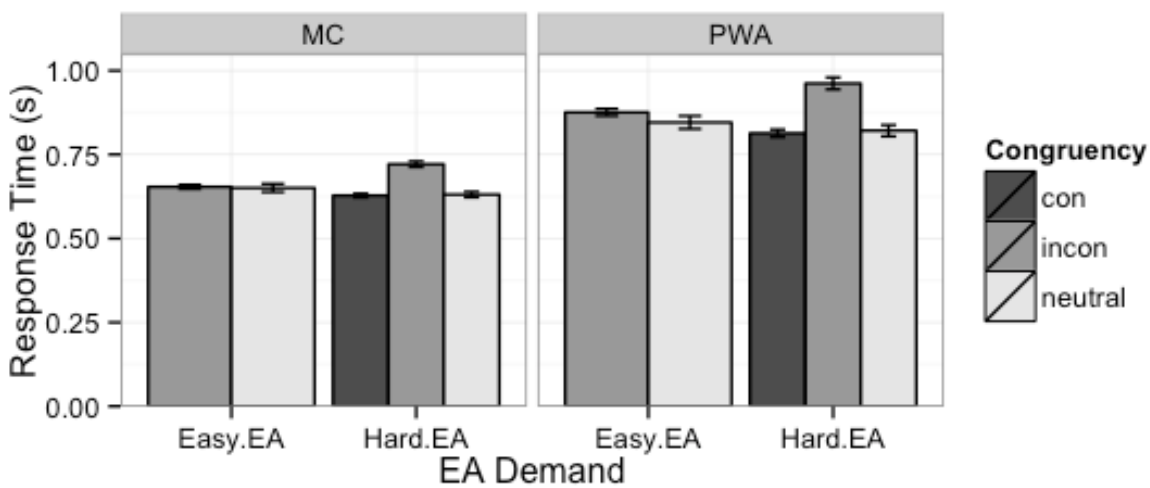
Inspection of the nested models determined that the 3-way interaction was due to the follow pattern of related interactions: differences in the interaction between congruency and group based on EA demand (models 11.1.2 and 11.1.3), and differences in the interaction effect between group and EA demand based on congruency type (models 11.1.6 and 11.1.7). PWA demonstrated larger interference effects than MCs in the hard EA ($p = 0.002$) but not easy EA ($p = 0.285$) condition. There was a group x EA demand interaction on incongruent trials, with PWA performing disproportionately worse in the hard EA condition ($p < 0.001$), but no such effect for neutral trials ($p = 0.52$). These results support a clear task maintenance deficit in PWA for this experiment, as initially predicted. However, the lack of interaction effects between group and congruency in the easy EA demand condition (model 11.1.2) indicate that conflict resolution deficits were not present in this group.

*11.3.2. Response times*

Visual inspection of raw response times via quantile-quantile plots by subject revealed a small number of extreme outliers and a general rightward skew of the response distributions. Therefore, cutoffs were set with responses below 200 ms and above 5000 ms dropped prior to analysis (less than 0.2% of trials), and response times were log-transformed prior to analyses. Mean raw response times rates by group, EA demand, and semantic category are presented in figure 11.3.

**Figure 11.3. Experiment 4: Spatial Stroop. Response time (s) by group, EA demand, and congruency.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008). Easy EA condition presented trials blocks with 76% incongruent stimuli, while hard EA condition presented trial bocks with 24% incongruent stimuli.




Log-transformed response times were analyzed using the same approach as for the accuracy data, except that linear mixed-effect regressions were used. The primary model tested for the presence of a 3-way interaction between the fixed effects of group, EA demand, and congruency (neutral vs. incongruent trials), followed by the same series of nested 2-way interaction models to investigate lower-order model effects and for comparison to accuracy data (table 11.2).

In contrast to accuracy results, the 3-way interaction for response times was not significant ($p = 0.872$; model 11.2.1). Investigation of the nested models determined that that PWA and MC groups both showed a robust task maintenance effect between EA demand and congruency ($p$s < 0.001; models 11.2.4 and 11.2.5). This indicates that while PWA were sensitive to EA demands on response times, they did not demonstrate a task maintenance deficit. In the group by congruency interaction models run separately by EA demand (11.2.2 and 11.2.3), both show trends for increased interference effects for PWA compared to controls ($p$s < 0.12), which could be interpreted as evidence for a conflict resolution deficit. However, looking at this interaction collapsing across EA demand conditions did not change the significance of this effect ($p = 0.105$), and the *Bits of Evidence* = 1.13 which are only very weakly in favor of this interaction over the null effect (model not presented).

**Table 11.2. Experiment 4: Spatial Stroop. Fixed effect estimates from linear mixed-effect models of response time on group, EA demand, and congruency. Group x EA demand x Congruency interaction.**

| | Estimate | Std. Error | Est. df | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| **11.2.1 Group x EA demand x congruency** | | | | | |
| (Intercept) | -0.48 | 0.04 | 42.5 | -13.4 | <0.001 |
| Congruency | 0.01 | 0.01 | 25275.0 | 2.0 | 0.043 |
| EA Demand | -0.01 | 0.03 | 46.3 | -0.5 | 0.620 |
| Group | 0.23 | 0.05 | 42.5 | 4.5 | <0.001 |
| Congruency: EA Demand | 0.12 | 0.01 | 25275.0 | 12.3 | <0.001 |
| Congruency: Group | 0.03 | 0.01 | 25275.0 | 3.2 | 0.002 |
| EA Demand: Group | -0.01 | 0.04 | 46.3 | -0.3 | 0.766 |
| Congruency: EA Demand: Group | 0.00 | 0.01 | 25275.0 | 0.2 | 0.872 |
| *Bits of Evidence for interaction:* -2.85 | | | | | |
| *AIC:* 3548 | | | | | |
| **11.2.2 Group x Congruency in Easy EA Condition.** | | | | | |
| (Intercept) | -0.48 | 0.04 | 41.0 | -13.0 | <0.001 |
| Congruency | 0.01 | 0.01 | 41.0 | 1.1 | 0.291 |
| Group | 0.23 | 0.05 | 41.0 | 4.3 | <0.001 |
| Congruency: Group | 0.03 | 0.02 | 41.0 | 1.7 | 0.100 |
| **11.2.3 Group x Congruency in Hard EA Condition.** | | | | | |
| (Intercept) | -0.49 | 0.04 | 41.0 | -12.6 | <0.001 |
| Congruency | 0.14 | 0.01 | 40.9 | 10.2 | <0.001 |
| Group | 0.22 | 0.06 | 41.0 | 3.9 | <0.001 |
| Congruency: Group | 0.03 | 0.02 | 41.0 | 1.6 | 0.113 |
| **11.2.4 Congruency x EA Demand in MC Group.** | | | | | |
| (Intercept) | -0.48 | 0.03 | 23.5 | -15.9 | <0.001 |
| Congruency | 0.01 | 0.01 | 13552.0 | 2.3 | 0.019 |
| EA Demand | -0.01 | 0.02 | 28.4 | -0.8 | 0.417 |
| Congruency: EA Demand | 0.12 | 0.01 | 13552.0 | 14.3 | <0.001 |

| | | | | | |
|---|---|---|---|---|---|
| **11.2.5 Congruency x EA Demand in PWA Group.** | | | | | |
| (Intercept) | -0.24 | 0.05 | 20.4 | -5.4 | <0.001 |
| Congruency | 0.04 | 0.01 | 11721.0 | 5.5 | <0.001 |
| EA Demand | -0.02 | 0.04 | 20.8 | -0.7 | 0.514 |
| Congruency: EA Demand | 0.13 | 0.01 | 11721.0 | 10.3 | <0.001 |
| **11.2.6 Group x Congruency interaction for Neutral trials.** | | | | | |
| (Intercept) | -0.48 | 0.04 | 41.0 | -13.0 | <0.001 |
| EA Demand | -0.01 | 0.03 | 40.9 | -0.5 | 0.627 |
| Group | 0.23 | 0.05 | 41.0 | 4.3 | <0.001 |
| EA Demand: Group | -0.01 | 0.04 | 41.0 | -0.3 | 0.772 |
| **11.2.7 Group x Congruency interaction for Incongruent trials.** | | | | | |
| (Intercept) | -0.47 | 0.04 | 41.1 | -13.1 | <0.001 |
| EA Demand | 0.11 | 0.02 | 41.0 | 4.7 | <0.001 |
| Group | 0.26 | 0.05 | 41.0 | 5.1 | <0.001 |
| EA Demand: Group | -0.01 | 0.03 | 41.0 | -0.3 | 0.801 |

Note: Initial version of model 11.2.1 obtained a convergence warning, and a model with simplified random effects structure is presented. Reference value for Group= MC, reference value for EA Demand = Hard EA.

## 11.4. Discussion

Experiment 4 manipulated the proportion of incongruent trials in a spatial Stroop task to investigate the executive attention abilities of PWA in the visuospatial domain. Both MCs and PWA demonstrated the expected proportion congruent effects based on interactions between EA demand and congruency: blocks with increased proportion of incongruent trials were associated with decreased interference effects in both response times and accuracy.

The PWA group performed worse than controls on this task overall, with lower accuracy rates and longer response times. Although there was no compelling evidence for a conflict resolution deficit, PWA demonstrated the predicted task maintenance deficit in response accuracy, with interference effects and performance on incongruent trials significantly greater than MCs in the hard EA condition but not the easy EA condition.

These results are in contrast to those from experiment 3, where PWA did not show the predicted task maintenance deficits, and instead showed impaired performance in the hard EA condition on neutral trials and when collapsing across congruency types. It was suggested that these results were due to difficulty forming appropriate stimulus response bindings, which is potentially consistent with the current results, as the stimulus-response binding demands were lower in experiment 4. This was due to the fact that stimulus-internal information was naturally paired to the response (*If the arrow is pointing to the LEFT, press the "Left" key on the keyboard*), and that there were also a smaller number of potential stimuli configurations to learn the mappings for: two arrow directions and three spatial locations allowed for six possible configurations, while the combination of target words and pictures types allowed for 40 unique stimuli configurations in the hard EA conditions of experiment 3. If this interpretation is correct, then greater stimulus-response mapping demands in experiment 3 could have obscured underlying effects of a domain-general task maintenance deficit observable in experiment 4. Alternately, a domain-specific visuospatial task maintenance deficit would also be consistent with the current findings. This is in principle a testable hypothesis. Follow-up work could manipulate stimulus response mapping demands while holding interference effects constant.

Please refer to Chapter 12 for direct statistical comparison of results from experiment 3 and experiment 4, as well as general discussion regarding the overall implications of these executive attention measures.

# CHAPTER TWELVE

## Domain Specificity in Executive Attention

The last four chapters have reviewed the results of each executive attention experiment individually. In experiments 1 and 2, semantic and perceptual SART tasks, PWA performed worse than controls on accuracy in both easy and hard executive attention conditions, suggesting a sustained attention or other form of domain-general impairment.

In experiment 3: Word-Picture Interference, PWA did not demonstrate the hypothesized task maintenance or conflict resolution deficits. Instead, they showed impaired performance on neutral trials in hard EA condition, which was attributed to deficits in forming and maintaining stimulus response mappings, as opposed to deficits in the aspects of task maintenance that allow the exertion of proactive control.

In experiment 4: Spatial Stroop, PWA did not demonstrate the hypothesized task conflict resolution deficit, but they did demonstrate the predicted task maintenance deficit on response accuracy. It was argued that differences in stimulus-response mapping demands between experiments 3 and 4 were responsible for these divergent findings, which masked an underlying task maintenance deficit that would have been otherwise apparent in experiment 3.

Overall, these experiments were designed to test the partial-encapsulation hypothesis of executive attention deficits in PWA, which was as follows:

> Task maintenance and conflict resolution impairments both exist in PWA following stroke, but task maintenance is a domain-general capacity whereas conflict resolution is at least partially domain-specific. Therefore, PWA should demonstrate worse performance than controls in both semantic (experiment 1: Semantic SART and experiment 3: Word-Picture Interference) and nonverbal (experiment 2: perceptual SART and experiment 4: Spatial Stroop) measures of task maintenance. In contrast, it is predicted that domain-specific conflict resolution deficits will cause PWA to demonstrate increased interference effects in the semantic but not nonverbal tasks.

As summarize above, many of these predictions have already been falsified in analyses focusing on individual experiments. However, given the divergent findings in experiments 3 and 4, it is especially important to make direct statistical comparisons across experiments before drawing any final conclusions. Therefore, section 12.1 compares these experiments on response accuracy, the major locus of reported effects between experiments 1 and 2 and between experiments 3 and 4.

In addition to these cross-experiment analyses, section 12.2 will address the same basic hypotheses using a case series approach. Given the degree of PWA sample heterogeneity, it is quite possible initial hypotheses could be confirmed or denied at the individual level. To review, it was claimed that at least some PWA would demonstrate dissociations in conflict resolution, with intact performance on nonverbal conflict resolution and impaired performance on semantic conflict resolution. However, given the claim that task maintenance is domain-general, individual PWA were not expected to show impairments in task maintenance in one domain but not the other.

## 12.1. Group-level accuracy comparisons

### *12.1.1. Comparison of experiments 1 and 2.*

Mean accuracy rates for group and stimuli type, separately by experiment are presented in figures 12.1 and 12.2 (reprinted from their respective chapters, for convenience). Data were evaluated via mixed-effect logistic regression in a 3-way interaction model looking at the interaction between group, experiment (semantic vs. perceptual domains in experiments 1 and 2, respectively), and response category (frequent category: animals and *O*'s vs. infrequent category: foods or *X*'s), presented in table 12.1.

Model results revealed a significant 3-way interaction ($p = 0.01$), which was interpreted based on results reported in chapters 8 and 9 and on two additional nested models that tested the interaction between EA demand and experiment separately by group (table 12.1). Inspection of the nested models determined that the 3-way interaction was due to a domain by EA demand interaction present for PWA, but not for MCs, which was driven by their disproportionately poor performance on the Low EA demand semantic condition.

**Figure 12.1. Experiment 1: Semantic SART Accuracy by Group and EA Demand.**

Figure reprinted from chapter 8.

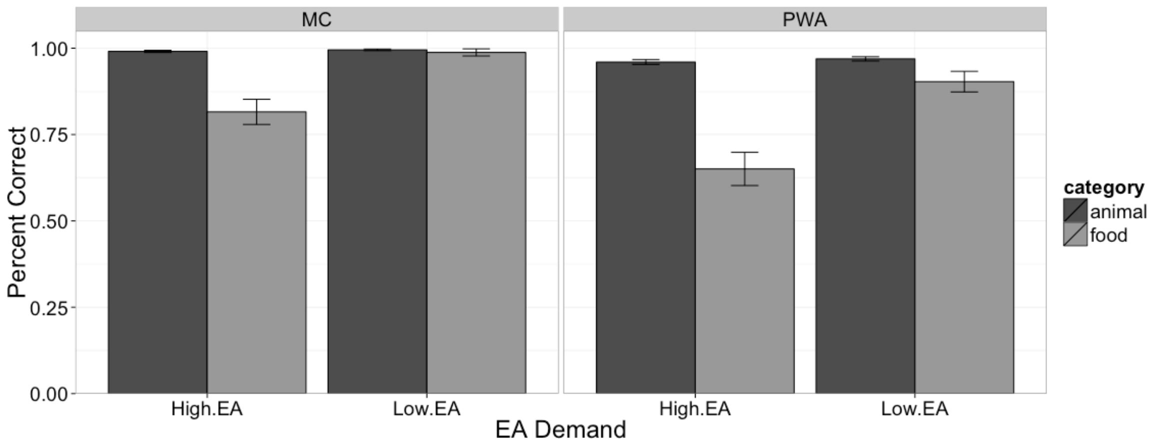



**Figure 12.2. Experiment 1: Perceptual SART Accuracy by Group and EA Demand.**

Figure reprinted from chapter 9.

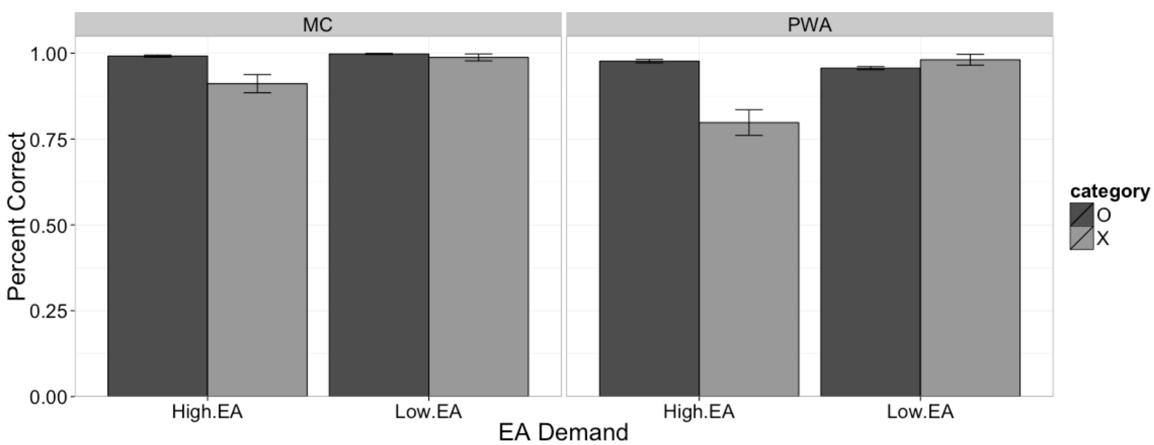


**Table 12.1. Comparison of Experiments 1 and 2. Fixed effect estimates from logistic mixed-effect models of response accuracy on group, EA demand, and domain.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **12.1.1 EA demand x Group x Domain** | | | | |
| (Intercept) | 2.69 | 0.27 | 9.82 | <0.001 |
| EA Demand | 2.19 | 0.41 | 5.39 | <0.001 |
| Group | -0.93 | 0.38 | -2.47 | 0.013 |
| Domain | -1.06 | 0.26 | -4.17 | <0.001 |
| EA Demand: Group | 0.57 | 0.54 | 1.06 | 0.290 |
| EA Demand: Domain | 0.80 | 0.56 | 1.43 | 0.153 |
| Group: Domain | -0.05 | 0.34 | -0.14 | 0.885 |
| EA Demand: Group: Domain | -1.77 | 0.69 | -2.56 | 0.011 |
| *AIC: 2393* | | | | |
| **12.1.2 Congruency x EA Demand in MC Group.** | | | | |
| (Intercept) | 2.69 | 0.27 | 9.90 | <0.001 |
| EA Demand | 2.18 | 0.41 | 5.33 | <0.001 |
| Domain | -1.13 | 0.24 | -4.75 | <0.001 |
| EA Demand: Domain | 0.78 | 0.57 | 1.37 | 0.170 |
| **12.1.3 Congruency x EA Demand in PWA Group.** | | | | |
| (Intercept) | 1.77 | 0.29 | 6.21 | <0.001 |
| EA Demand | 2.77 | 0.36 | 7.70 | <0.001 |
| Domain | -1.10 | 0.28 | -3.98 | <0.001 |
| EA Demand: Domain | -0.95 | 0.41 | -2.31 | 0.021 |

Note: Initial version of models obtained convergence warnings and models with simplified random effects structures with random intercepts only are presented. Reference value for Group= “MC”, reference value for EA Demand = “easy EA”, reference value for Domain = “Perceptual”.

### *12.1.2. Comparisons of experiments 3 and 4.*

Mean accuracy rates for group and stimuli type separately by experiment are presented in figures 12.3 and 12.4 (reprinted from their chapters 10 and 11, for convenience). Data were evaluated via mixed-effect logistic regression in a 4-way interaction model looking at the interaction between group, experiment (semantic vs. perceptual domain for experiments 3 vs. 4, respectively), EA demand (based on congruency proportion), and stimuli congruency, presented in table 12.2. Model results did not reveal a significant 4-way interaction ($p$ = 0.20).

**Figure 12.3. Experiment 3: Word-Picture Interference. Accuracy by Group, EA demand, and Congruency.**

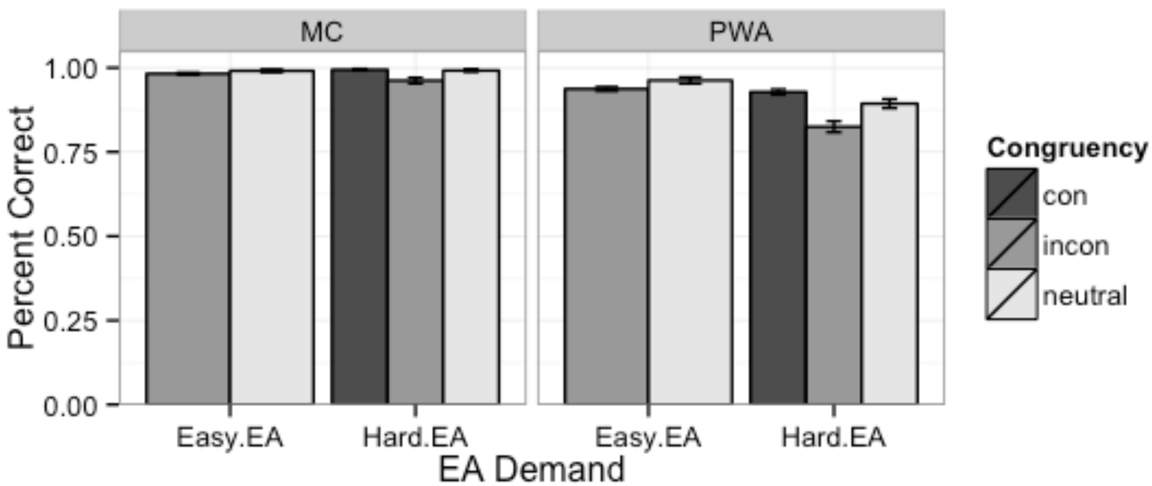



**Figure 12.4. Experiment 4: Spatial Stroop. Accuracy by Group, EA demand, and Congruency.**

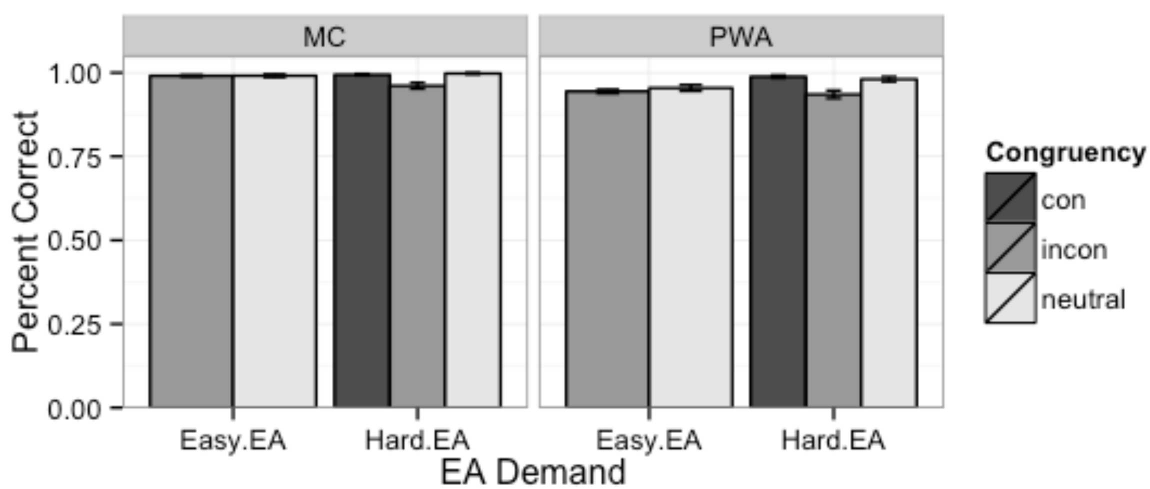


**Table 12.2. Comparison of Experiments 3 and 4. Fixed effect estimates from logistic mixed-effect models of response accuracy on group, EA demand, Congruency, and domain.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **12.1.1 EA demand x Group x Domain** | | | | |
| (Intercept) | 3.68 | 0.46 | 8.04 | <0.001 |
| Congruency | 2.93 | 0.48 | 6.08 | <0.001 |
| EA demand | 1.47 | 0.17 | 8.68 | 0.00 |
| Group | -0.33 | 0.39 | -0.85 | 0.396 |
| Domain | 0.08 | 0.42 | 0.19 | 0.846 |
| Congruency: EA demand | -2.89 | 0.56 | -5.19 | <0.001 |
| Congruency: Group | -1.60 | 0.52 | -3.06 | 0.002 |
| EA demand: Group | -1.32 | 0.21 | -6.43 | <0.001 |
| Congruency: Domain | -1.12 | 0.60 | -1.89 | 0.059 |
| EA demand: Domain | -0.67 | 0.22 | -2.98 | 0.003 |
| Group: Domain | -1.35 | 0.20 | -6.71 | <0.001 |
| Congruency: EA demand: Group | 1.80 | 0.61 | 2.94 | 0.003 |
| Congruency: EA demand: Domain | 1.98 | 0.67 | 2.97 | 0.003 |
| Congruency: Group: Domain | 0.64 | 0.60 | 1.06 | 0.287 |
| EA demand: Group: Domain | 1.86 | 0.27 | 6.94 | <0.001 |
| Congruency: EA demand: Group: Domain | -0.95 | 0.74 | -1.29 | 0.196 |
| *AIC: 13153* | | | | |

Note: Initial version of models obtained convergence warnings and models with simplified random effects structures with random intercepts only are presented. Reference value for Group= “MC”, reference value for EA Demand = “easy EA”, reference value for Domain = “Perceptual”.

Overall, comparison of experiments 1 and 2 confirms the conclusion drawn from the by-experiment analyses, and indicates that PWA demonstrate a semantic deficit above and beyond their sustained attention deficits. For experiments 3 and 4, the lack of a significant 4-way interaction may merely be an issue of statistical power issue, but if not, may be interpreted as indirect support for the claim that executive attention task maintenance deficits did in fact have an influence on experiment 3, but were masked by the influence of additional stimulus-response mapping demands.

### 12.2. Case-series Comparisons

In addition to the group-level analyses, individual cases were also examined for patterns of association and dissociation in executive attention. Table 12.5 presents case series data regarding individual impairments in task maintenance and conflict resolution across experiments 1 through 4. *t* values in table 12.5 were calculated using difference scores within each experiment based on the same contrasts examined in the group-level analyses (tables 12.3 and 12.4; see table notes for further description regarding calculation methods). Using these difference scores, PWA were then compared to MC group performance while correcting for sample size, based on the methods of Crawford and Howell (1998). This approach establishes expected ranges of normal performance based on the mean, standard deviation, and number of control participants.

Given the large number of PWA in this case series, two thresholds for significance are presented in table 12.5: *t* values meeting an uncorrected two-tailed significant threshold of alpha = .05 are highlighted in outlined cells, and are considered "weak" evidence for individual impairment. As a more stringent criterion, shaded cells indicate significance at a Bonferroni-adjusted alpha based on 20 simultaneous tests, and are considered "strong" evidence for impairment. Findings will be discussed with emphasis on "strong" impairments in an attempt to provide as rigorous a test of hypotheses as possible, although it should be noted that the "weak" unadjusted thresholds generally supports similar (if slightly noisier) conclusions, and are provided for reference.

**Table 12.3. Individual PWA response accuracy and task maintenance scores (percent correct), as reflected by difference scores in SART experiments 1 and 2.**

| | Experiment 1: SSART | | Experiment 2: PSART | |
|---|---|---|---|---|
| | Hard EA Condition | Task Maintenance Score | Hard EA Condition | Task Maintenance Score |
| PWA3 | 96 | 0 | 88 | 8 |
| PWA4 | 56 | 44 | 92 | 4 |
| PWA5 | 44 | 56 | 84 | 16 |
| PWA6 | 84 | -12 | 76 | 24 |
| PWA7 | 68 | 8 | 68 | 32 |
| PWA9 | 56 | 32 | 100 | 0 |
| PWA10 | 88 | 12 | 96 | 4 |
| PWA11 | 80 | 20 | 96 | 4 |
| PWA12 | 16 | 52 | 84 | 16 |
| PWA13 | 88 | -12 | 100 | -8 |
| PWA14 | 28 | 72 | 40 | 60 |
| PWA15 | NA | NA | 56 | 44 |
| PWA16 | 84 | 16 | 84 | 16 |
| PWA18 | 56 | 44 | 96 | 4 |
| PWA19 | 72 | 8 | 92 | 8 |
| PWA20 | 92 | 8 | 96 | 4 |
| PWA21 | 48 | 28 | 88 | 4 |
| PWA22 | 32 | 52 | 56 | 44 |
| PWA23 | 56 | 44 | 76 | 24 |
| PWA24 | 92 | 8 | 84 | 16 |

Note: task maintenance scores calculated by subtracting performance on the Hard EA condition from performance on the Easy EA condition for the infrequent category ("Foods" and "*X*s", respectively). Therefore, accuracy only presented by participant for Hard EA condition and task maintenance score; performance on the Easy EA condition may be calculated from the above by adding the task maintenance and Hard EA columns for a given experiment. Larger scores indicate greater difficulty (i.e., scores can be thought of as reflecting the "cost" of an individual attempting to maintain task).

**Table 12.4. Individual PWA difference scores on responses accuracy (percent correct) for experiments 3 and 4 reflecting task maintenance and conflict resolution ability.**

| | **Task Maintenance** | | **Conflict Resolution** | |
|---|---|---|---|---|
| | Expt 3: WPI | Expt 4: SpStroop | Expt 3: WPI | Expt 4: SpStroop |
| PWA3 | 12.3 | 15.2 | 1.2 | -1.7 |
| PWA4 | 0.7 | 0.3 | 0.3 | -0.3 |
| PWA5 | 1.8 | 7.7 | 1.3 | 4.8 |
| PWA6 | 2.0 | 11.2 | 0.1 | 2.4 |
| PWA7 | 7.8 | 5.3 | 2.6 | -1.1 |
| PWA9 | 2.9 | 5.8 | -0.4 | 0.6 |
| PWA10 | -1.0 | 0.4 | 1.0 | 0.6 |
| PWA11 | 1.8 | -0.3 | 1.3 | 0.3 |
| PWA12 | 13.0 | 0.0 | 29.7 | 0.0 |
| PWA13 | 3.1 | -0.3 | -1.0 | 0.3 |
| PWA14 | -1.5 | -2.6 | 1.5 | 2.6 |
| PWA15 | 5.6 | -2.6 | 1.7 | 3.6 |
| PWA16 | 1.1 | -1.0 | 1.0 | 1.0 |
| PWA18 | 3.8 | 0.5 | 0.3 | 1.6 |
| PWA19 | 0.5 | 2.8 | 4.2 | -0.7 |
| PWA20 | 0.1 | 0.4 | -0.1 | -0.4 |
| PWA21 | 4.9 | -0.6 | 0.5 | 0.6 |
| PWA22 | 31.6 | 21.7 | 1.6 | 4.3 |
| PWA23 | 1.0 | 2.6 | 1.1 | 2.6 |
| PWA24 | -3.6 | 2.6 | 2.5 | 0.5 |

Note: Conflict resolution calculated by subtracting performance on incongruent trials from performance on neutral trials (a measure of interference) in the Easy EA conditions. Task maintenance calculated by first determining the interference effect in the Hard EA condition (neutral- incongruent), then by subtracting this score from the conflict resolution score. In both cases, larger scores indicate greater difficulty (i.e., scores can be thought of as reflecting the "cost" of an individual attempting to maintain task or resolve conflict).

**Table 12.5. *t*-values for tests of task maintenance and conflict resolution deficits on individual PWA.**

| | Task Maintenance | | | | Conflict Resolution | |
|---|---|---|---|---|---|---|
| | Expt 1: SSART | Expt 2: PSART | Expt 3: WPI | Expt 4: SpStroop | Expt 3: WPI | Expt 4: SpStroop |
| PWA10 | -0.48 | -0.47 | -0.94 | -0.76 | 0.07 | 0.70 |
| PWA11 | 0.26 | -0.47 | -0.09 | -0.95 | 0.26 | 0.37 |
| PWA12 | 3.19 | 1.07 | 3.29 | -0.86 | 16.61 | -0.04 |
| PWA13 | -2.68 | -2.01 | 0.30 | -0.95 | -1.10 | 0.37 |
| PWA14 | 5.02 | 6.73 | -1.11 | -1.48 | 0.38 | 3.11 |
| PWA15 | NA | 4.67 | 1.07 | -1.48 | 0.45 | 4.36 |
| PWA16 | -0.11 | 1.07 | -0.31 | -1.10 | 0.07 | 1.17 |
| PWA18 | 2.45 | -0.47 | 0.52 | -0.75 | -0.31 | 1.91 |
| PWA19 | -0.84 | 0.04 | -0.49 | -0.20 | 1.93 | -0.91 |
| PWA20 | -0.84 | -0.47 | -0.63 | -0.78 | -0.53 | -0.51 |
| PWA21 | 0.99 | -0.47 | 0.83 | -1.01 | -0.23 | 0.69 |
| PWA22 | 3.19 | 4.67 | 8.93 | 4.30 | 0.45 | 5.26 |
| PWA23 | 2.45 | 2.10 | -0.35 | -0.25 | 0.14 | 3.18 |
| PWA24 | -0.84 | 1.07 | -1.72 | -0.24 | 0.95 | 0.57 |
| PWA3 | -1.58 | 0.04 | 3.09 | 2.76 | 0.20 | -2.08 |
| PWA4 | 2.45 | -0.47 | -0.43 | -0.81 | -0.31 | -0.35 |
| PWA5 | 3.55 | 1.07 | -0.09 | 0.96 | 0.26 | 5.86 |
| PWA6 | -2.68 | 2.10 | -0.05 | 1.79 | -0.43 | 2.86 |
| PWA7 | -0.84 | 3.13 | 1.72 | 0.39 | 1.02 | -1.38 |
| PWA9 | 1.35 | -0.98 | 0.24 | 0.51 | -0.73 | 0.67 |

Note: *t*-values determined based on difference scores reported in tables 12.3 and 12.4, using the methods of Crawford and Howell (1998). Outlined cells meet criteria for impairment at unadjusted two-tailed alpha of 0.05; shaded cells meet criteria for impairment after Bonferroni Adjustment for 20 tests (alpha = 0.0026). PWA15 was unable to complete experiment 1 (0% accuracy on both the Low EA-Food and High EA-Animal conditions).

Using the Bonferroni-adjusted criteria, there was only one patient, PWA5, who showed a dissociation between SART experiments 1 and 2; he showed impaired performance only on 2 of the 6 executive attention measures; task maintenance on experiment 1 and conflict resolution in experiment 4. Examination of his standard testing scores did not indicate any specific patterns to account for this, as they scored at ceiling or in the typical range on all administered tasks. However, examination of participant testing schedules revealed one possible explanation for this pattern: experiments were presented to all participants in one of two counterbalanced orders to control for fatigue effects across participants, and total experiment participation time in a given day was capped at 2.5 hours. These constraints meant that the majority participants had executive attention experiments split across two days of testing. However, three of the fastest PWA (PWA4, PWA5, and PWA16) received all 4 executive attention experiments on a single day. For PWA5, experiments 1 and 4 were the last two administered in that single session, and were the two tests on which he demonstrated impairment. Review of their testing log also revealed that PWA5 stated they felt particularly fatigued by the end of the session. Therefore, it is likely that this dissociation in task maintenance for SART tasks was due to fatigue, and not to domain-specific task maintenance deficits.

Of the other three PWA who demonstrated strong impairments on experiments 1 or 2, PWA15 was unable to complete experiment 1, making direct comparisons impossible, PWA14 showed strong impairments in both experiments, and PWA22 showed a strong impairment for experiment 2 and a weak impairment for experiment 1. Overall, these results are interpreted as supporting domain-general executive attention in

SART-like contexts; i.e., in contexts where task maintenance is required in order to inhibit habituated motor responses.

Looking at task maintenance effects for experiments 3 and 4 reveal only one case with strong impairments, PWA22, who was impaired across both experiments. This finding, and the lack of strong dissociations on other PWA for these tasks is interpreted as evidence for domain-general executive attention in Stroop-like contexts in where specific stimulus properties require active suppression.

In contrast, examination of conflict resolution found no instances in which an individual was impaired for conflict resolution in both experiments 3 and 4, supporting the claim that this aspect of executive attention is domain specific.

These patterns at the individual level are also supported by correlations looking at task maintenance and conflict resolution within the PWA group, which showed significant positive relationships for task maintenance between experiments 1 and 2 ($r$ = .48) and between experiments 3 and 4 ($r$ = .71), but no significant relationship between conflict resolution measures in experiments 3 and 4 ($r$ = -.15).

## 12.3. Discussion

At the group level, there was only inconsistent evidence for executive attention impairments, with experiment 4 showing evidence for task maintenance deficits. Instead, group PWA performance seemed more consistent with difficulties in stimulus-response mapping not specifically involved in interference resolution. This was previously argued based on the results from experiment 3, but it is also consistent with the general pattern of impaired performance across easy and hard executive attention conditions for experiments 1 and 2: although initially interpreted as evidence for a sustained attention deficit, it should be noted that these conditions also possess equivalent stimulus-response mapping demands, meaning that a deficit in stimulus-response mapping would affect these conditions equally.

Looking at this dataset at the level of individual cases shows that approximately half the sample was in the typical range across all measures of executive attention, which is somewhat unsurprising given the relatively mild presentation of many of these individuals. However, focusing on the individuals who did present with executive attention impairments supports the claim that task maintenance deficits are general across semantic and visuospatial domains within Stroop and within SART task types, and also supports the claim for domain-specific conflict resolution deficits within the Stroop task type.

# CHAPTER THIRTEEN

## Experiment 5: Lexical Decision with Varying Speed and Accuracy Instructions

### 13.1 Methods and Procedure for Experiment 5

#### *13.1.1. Materials and Design*

In Experiment 5, participants were required to make a lexical decision (word vs. nonword) on visually presented letter strings within different instruction and feedback task demands (neutral vs. speed-focused vs. accuracy-focused). This experiment was based on experiment 1 from Wagenmakers et al. (2008), but included the addition of a neutral baseline condition.

Stimuli were taken from Wagenmakers et al. (2008), and consisted of high frequency words (HF), low frequency words (LF), and nonwords created from high frequency and low frequency words (NWhigh and NWlow). A description of these same stimuli from Ratcliff et al. (2004) is as follows:

> The stimuli were taken from Ratcliff et al. (2004a). The word stimuli consisted of 814 high frequency words with frequencies ranging from 78 to 10,600 occurrences per million (mean = 323.37, SD = 641.42, Kucera & Francis, 1967), 858 low frequency words with frequencies of 4 and 5 occurrences per million (mean = 4.41, SD = .49), and 741 very low frequency words with frequencies of 1 or 0 occurrences per million (mean = 0.38, SD = .59). All the very low frequency words occurred in the Webster's Ninth Collegiate Dictionary (1990), and they were

> screened by three Northwestern undergraduate students—any words any one of the three students did not know were eliminated. For each word, a nonword was created by randomly replacing all vowels by other vowels (except for ‘‘u’’ after ‘‘q’’), resulting in a total of 2413 nonwords. (p. 144)

For the current experiment, 384 stimuli were selected at random from each of the above categories, for a total of 1440 experimental stimuli and 96 practice items. It should be noted that the original pool of stimuli did not control for length across frequency manipulations, but since this effect orthogonal to the primary hypotheses in the design of the current work, this potential confound was left unchanged (see table 13.1 for summary stimuli characteristics).

**Table 13.1. Experiment 5: Lexical Decision. Characteristics of word and nonword stimuli by task and stimuli type.**

| | | Frequency | | | Length | | |
|---|---|---|---|---|---|---|---|
| Task Condition | Stimuli Type | Mean | Min | Max | Mean | Min | Max |
| Neutral | HF | 3.72 | 1.60 | 5.47 | 5.83 | 4 | 10 |
| Neutral | LF | 1.72 | 0.30 | 3.43 | 6.81 | 4 | 11 |
| Neutral | NWhigh | - | - | - | 5.83 | 4 | 10 |
| Neutral | NWlow | - | - | - | 7.03 | 4 | 11 |
| Accuracy | HF | 3.77 | 1.81 | 5.52 | 5.53 | 4 | 10 |
| Accuracy | LF | 1.81 | 0.48 | 3.33 | 6.88 | 4 | 11 |
| Accuracy | NWhigh | - | - | - | 5.83 | 3 | 10 |
| Accuracy | NWlow | - | - | - | 6.97 | 4 | 11 |
| Speed | HF | 3.65 | 2.20 | 5.70 | 6.07 | 4 | 12 |
| Speed | LF | 1.82 | 0.70 | 3.23 | 6.88 | 4 | 11 |
| Speed | NWhigh | - | - | - | 5.51 | 4 | 10 |
| Speed | NWlow | - | - | - | 7.02 | 4 | 11 |

Note: Mean and maximum/minimum values for word and nonword sting length in characters. For words, frequency presented as log base10 word frequency ("Lg10WF", Subtlexus database; Brysbaert & New, 2009).

Overall, Experiment 5 employed a 3x4x2 mixed factorial design, with task contexts (neutral vs. speed-focused vs. accuracy-focused) and stimuli type (HF vs. LF vs. NWhigh vs. NWlow) as within-subject factors, and group (PWA vs. MC) as a between-subject factor. The ability to adapt and respond to task demands was assessed by comparing performance between task contexts, while the ability to process lexical information was assessed by comparing performance differences between stimuli types.

### *13.1.2. Procedure*

For each participant, stimuli were presented in a total of 15 experimental blocks of 96 trials each. Each block contained 24 stimuli of each type (HF, LF, NWhigh, NWlow). Each participant was given the same block order, with trials randomized within each block. The first 5 blocks were presented under 'neutral' task instructions stressing both speed and accuracy, while the remaining 10 blocks alternated between instructions stressing speed and instructions stressing accuracy. A short break was offered between each block.

Each trial was preceded by a 150 ms pre-trial interval, and stimuli stayed on the screen until the participant made a response, either by pressing the "left" keyboard key to indicate a word or the "right" keyboard key to indicate a nonword. In accuracy-focused blocks, the word "INCORRECT" appeared in blue font for 800ms following an error response, while in speed-focused blocks, the words "RESPOND FASTER" appeared in blue font for 800ms following a slow response. This speed feedback threshold was determined for each participant by calculating their 70$^{th}$ quantile for response times in the initial neutral condition blocks.

Each condition was preceded by a set of written instructions that were read to participants. On neutral blocks, participants were asked to respond both as quickly and as accurately as possible. On accuracy blocks, participants were asked to respond as accurately as possible. On speed blocks, participants were asked to respond as quickly as possible while still classifying the stimuli. Participants received 32 trials of practice for each condition prior to encountering it for the first time. A short break was offered between each block, and participants were provided again with task auditory and written instructions before beginning the subsequent block.

## 13.2. Statistical and Modeling Techniques

Analysis of accuracy and response time data followed the methods of experiment 1, including data cleaning procedures and statistical models.

Diffusion models were fit to the data using the *fast-dm-30* program (Voss et al., 2015), with estimated response distributions generated for best-fitting diffusion model parameters via version 0.2-6 of the 'rtdists' R package (Brown et al., 2014).

## 13.3. Results

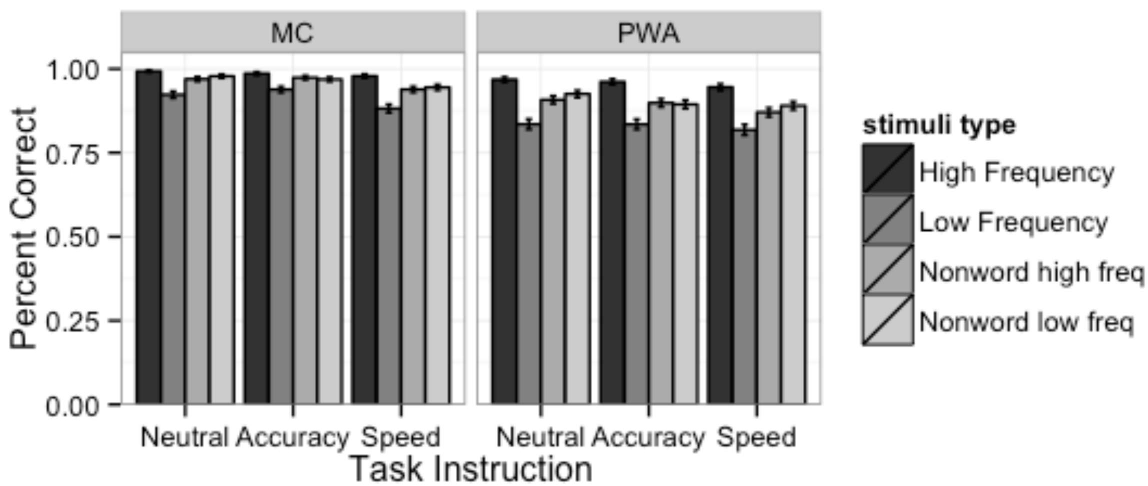
Analyses were conducted on the full set of 20 PWA and 23 MCs.

### *13.3.1. Accuracy*

Mean accuracy rates by group, stimuli type, and task are presented in figure 13.1. Accuracy data were evaluated between groups via mixed-effect logistic regression in separate 2-way interaction models, looking at the interaction between group and stimuli type, and at the interaction between group and task (table 13.2).

**Figure 13.1. Experiment 5: Lexical Decision. Accuracy by group, stimuli type, and task.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).




Model results revealed a significant 2-way interaction between task and group, such that PWA performed better on the neutral vs. accurate conditions compared to controls (PWA mean response accuracy 91% for neutral condition and 90% for the accurate condition, compared to MC mean response accuracy of 97% for both conditions; $p = 0.047$), and also showed less of a performance decrement in the speed compared to accuracy condition (PWA performance 90% vs. 88%, compared to 97% vs. 94% in MCs; $p < 0.001$). Although PWA were less accurate overall across stimuli types, there was no interaction between group and stimuli type (*p*s > 0.1).

**Table 13.2. Experiment 5: Lexical Decision, primary analyses of response accuracy.**

Fixed effect estimates from logistic mixed-effect models of response accuracy on group, task, and stimuli type.

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **13.2.1 Group x Task** | | | | |
| (Intercept) | 4.29 | 0.20 | 21.98 | <0.001 |
| TaskNeutral | -0.03 | 0.11 | -0.27 | 0.790 |
| TaskSpeed | -0.87 | 0.10 | -8.63 | <0.001 |
| Group | -1.46 | 0.27 | -5.39 | <0.001 |
| TaskNeutral: Group | 0.19 | 0.09 | 1.99 | 0.047 |
| TaskSpeed: Group | 0.62 | 0.08 | 7.34 | <0.001 |
| *AIC:* 26044 | | | | |
| | | | | |
| **13.2.2 Group x Stimuli type** | | | | |
| (Intercept) | 4.95 | 0.21 | 23.95 | <0.001 |
| StimTypeLF | -1.91 | 0.12 | -15.56 | <0.001 |
| StimTypeNWhigh | -1.05 | 0.13 | -8.14 | <0.001 |
| StimTypeNWlow | -0.94 | 0.13 | -7.25 | <0.001 |
| Group | -1.19 | 0.28 | -4.23 | <0.001 |
| StimTypeLF: Group | 0.18 | 0.12 | 1.54 | 0.123 |
| StimTypeNWhigh: Group | -0.06 | 0.13 | -0.51 | 0.610 |
| StimTypeNWlow: Group | -0.03 | 0.13 | -0.25 | 0.800 |
| *AIC:* 25800 | | | | |

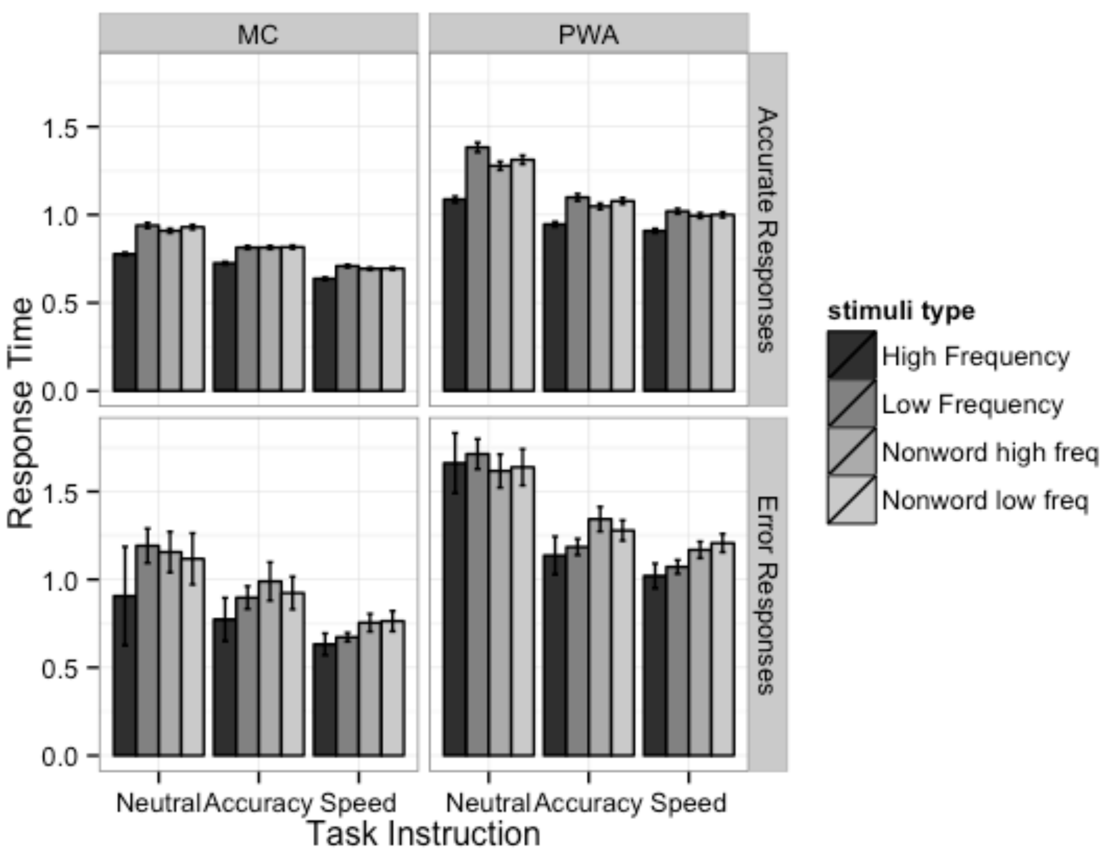
Note: Reference value for task = accuracy-focused condition; reference value for group=MC; reference value for stimuli type= HF (high frequency words). Initial version of models obtained convergence warnings and models with simplified random effects structures with random intercepts only are presented.

### *13.3.2. Response times*

Visual inspection of raw response times via quantile-quantile plots by subject revealed a small number of extreme outliers and a general rightward skew of the response distributions. Therefore, cutoffs were set and responses below 200 ms and above 4000 ms were dropped prior to analysis (less than 0.7% of trials). Although this upward cutoff boundary may be considered overly conservative in removing outliers given the generally short response times associated with the lexical decision in general (e.g., Ratcliff et al., 2004), quantile-quantile plots of log-transformed response times revealed clear linear relationships for a majority of subjects up through the upper threshold, and therefore was considered an acceptable balance in terms of including informative data (Baayen, 2008, pp. 265–266). Mean raw response times by group, condition, and response accuracy are presented in figure 13.3.

**Figure 13.2. Experiment 5: Lexical Decision with Varying Speed and Accuracy Instructions. Response time (s) by group, Stimuli type, and task.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).



Log-transformed response times were analyzed using the same approach as for the accuracy data, except that linear mixed-effect regression was used (table 13.3). Model results revealed a significant 2-way interaction between task and group, such that PWA took marginally longer than controls on the neutral compared to accurate condition ($p$ = 0.076), and showed less of a difference in the speed vs. accuracy conditions compared to controls ($p < 0.001$). PWA were slower overall across stimuli types, and there was evidence for a marginal significant interaction between group and stimuli type, with larger response time differences between the high and low frequency words for PWA ($p$ = 0.08).

**Table 13.3. Experiment 5: Lexical Decision, primary analyses of response time. Fixed effect estimates from linear mixed-effect models of log response time on group, task, and stimuli type.**

| | Estimate | Std. Error | Est. df | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| **13.3.1 Group x Task** | | | | | |
| (Intercept) | -0.27 | 0.03 | 42.13 | -7.83 | <0.001 |
| TaskNeutral | 0.10 | 0.03 | 44.15 | 3.37 | 0.002 |
| TaskSpeed | -0.14 | 0.02 | 49.71 | -7.48 | <0.001 |
| Group | 0.26 | 0.05 | 41.00 | 5.22 | <0.001 |
| TaskNeutral: Group | 0.08 | 0.04 | 41.00 | 1.82 | 0.076 |
| TaskSpeed: Group | 0.09 | 0.03 | 40.99 | 3.26 | 0.002 |
| *AIC:* 15721 | | | | | |
| **13.2.2 Group x Stimuli type** | | | | | |
| (Intercept) | -0.38 | 0.03 | 44.17 | -11.51 | <0.001 |
| StimTypeLF | 0.13 | 0.02 | 81.37 | 7.98 | <0.001 |
| StimTypeNWhigh | 0.11 | 0.02 | 73.47 | 6.54 | <0.001 |
| StimTypeNWlow | 0.12 | 0.02 | 67.64 | 6.37 | <0.001 |
| Group | 0.30 | 0.05 | 41.00 | 6.47 | <0.001 |
| StimTypeLF: Group | 0.04 | 0.02 | 40.95 | 1.80 | 0.080 |
| StimTypeNWhigh: Group | 0.01 | 0.02 | 41.01 | 0.29 | 0.770 |
| StimTypeNWlow: Group | 0.01 | 0.02 | 40.99 | 0.60 | 0.554 |

Note: Reference value for task = accuracy condition; reference value for stimuli type= HF (high frequency words).

*13.3.3. Diffusion Models*

Diffusion model parameters were fit individually to each participant by entering their response time distributions for correct and error responses into *fast-dm-30* (Voss, Voss, & Lerche, 2015). For convenience, Voss et al.'s gloss of diffusion parameters is excerpted as follows in table 13.4:

**Table 13.4. Parameters of the Diffusion Model, typical ranges of values, and cognitive interpretation, as defined by fast-dm-30. Excerpted from Voss et al. (2015), p. 3.**

| Parameter | Fast-dm | Typical range | Interpretation |
|---|---|---|---|
| Drift | $v$ | −4 to +4 | average speed of information uptake |
| Threshold separation | $a$ | 0.6 to 2 | response caution |
| Starting point | $z_r$ | 0.4 to 0.6 | decision bias |
| Non-decisional constant | $t_0$ | 0.2 to 1.0 | duration of non-decisional processes |
| Difference in non-decisional constant | $d$ | −0.1 to +0.1 | response preparation/ response inhibition |
| Intertrial variability of drift | $s_v$ | 0 to 1 | differences in stimulus properties or fluctuations in attention |
| Intertrial variability of starting point | $s_{zr}$ | 0.0 to 0.5 | differences in expectations |
| Intertrial variability of non-decisional constant | $s_{t0}$ | 0 to 1 | differences in speed of response execution |

Diffusion model starting point ($z_r$), boundary/threshold separation (a), and nondecision time ($t_0$) were estimated separately by task, while drift rates ($v$) were estimated separately by task and stimuli type. All other parameters were held constant across conditions with the exception of *d*, which was not included in current models.

Model adequacy was evaluated per the recommendations of Voss et al. (2015), with predicted response time quantiles plotted against empirical quantiles for each condition in each participant.

For this approach, predicted response time distributions were derived by generating a 10,000-response sample for each by-participant set of diffusion parameters in each of the 12 conditions. The 25, 50, and 75 quantiles were then calculated for both empirical and predicted responses separately for correct and error responses, with results plotted by group in figures 13.3 and 13.4.

Voss et al. stated that, "When all data points are positioned near the main diagonal, a good fit can be assumed" (p. 7). Based on this rationale, current plots showed good fits for both groups across quantiles for correct responses. Fits appeared more variable for error responses, but still showed clear linear trends, and also appeared roughly equal across groups. The only possible exception to this were a small number of outliers for error responses in the 25 and 50 quantiles for the PWA group, which appeared to mostly be do to longer-than-predicted times for responses to nonwords in the neutral condition.

**Figure 13.3. Experiment 5: Lexical Decision. Empirical versus predicted response times for correct and error responses across all conditions for the PWA group.**

Note: good model fits are reflected by a linear relationship along the main diagonal.

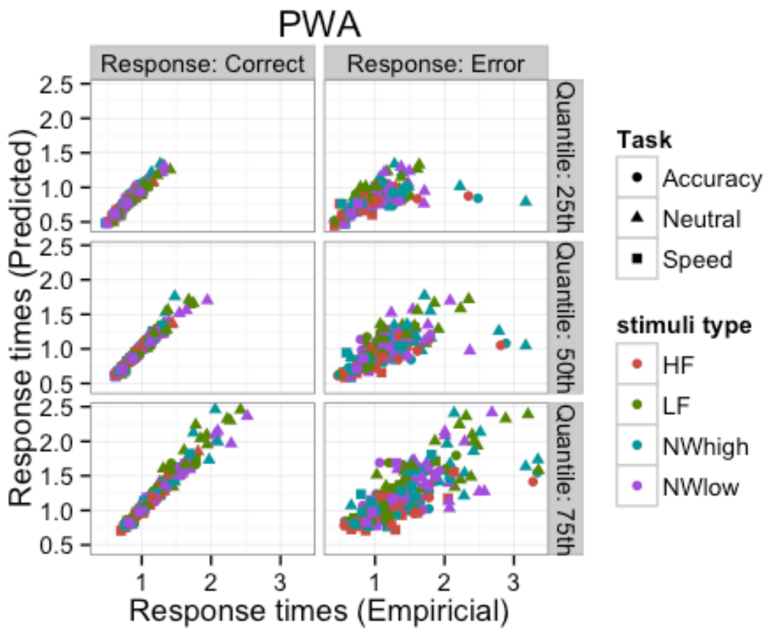
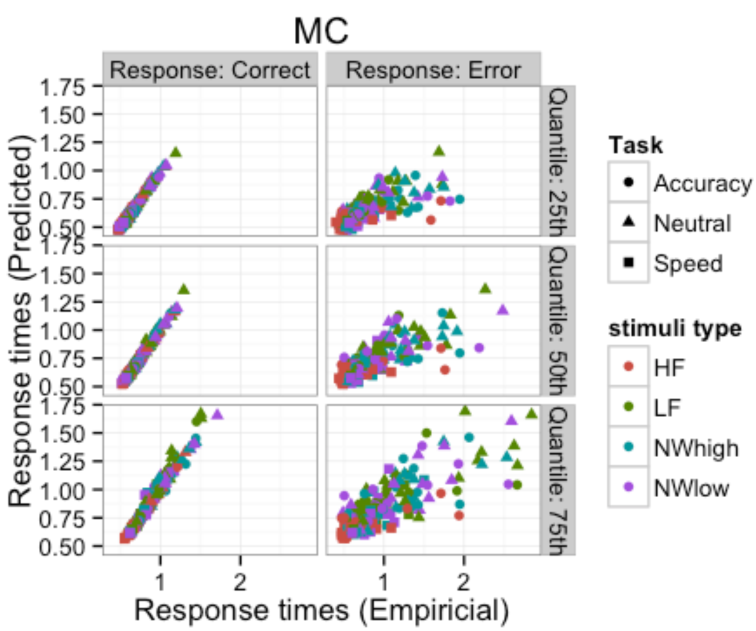



**Figure 13.4. Experiment 5: Lexical Decision. Empirical versus predicted response times for correct and error responses across all conditions for the MC group.**

Note: good model fits are reflected by a linear relationship along the main diagonal.



Mean parameter estimates by group are presented in table 13.4. Welch's Two Sample *t*-tests run separately by parameter and evaluated for significance based on an uncorrected alpha of 0.05 (table 13.4) showed that groups differed in the following contexts: in the neutral task condition for $z_r$ and $a$, the speed and accuracy task conditions for $t_0$, $st_0$, and for all conditions on $v$ ($p$s < 0.05). Groups did not differ in terms of $s_{zr}$, $s_v$, or $p$ ($p$s > 0.05).

Given these findings, group differences were further evaluated in the parameters that were allowed to vary between experimental conditions ($z_r$, $a$, $t_0$, and $v$) via separate two-way repeated-measures ANOVAs, crossing task and group for $z_r$ and $a$, and crossing stimuli type and group for $v$ (collapsing across task). There was no interaction between group and task for $z_r$, $F(2, 82) = 1.202$, $p = .306$, $\eta_p^2 = .01$. For $a$, there was a significant interaction between group and task, $F(2, 82) = 4.492$, $p = .014$, $\eta_p^2 = .026$. Post-hoc pairwise comparisons revealed that PWA set disproportionately high boundaries in the neutral compared to accuracy condition, but did not differ from MCs in differences between speed and accuracy conditions (figure 13.5). These models also replicated the general expected speed-accuracy effects on boundary width across groups, with speed focus leading to narrower boundary separation than accuracy focus ($p < 0.001$).

For $t_0$, there was a significant interaction between group and task, $F(2, 82) = 5.097$ , $p = .008$, $\eta_p^2 = .017$. Post-hoc pairwise comparisons revealed that nondecision times remained constant for PWA across task conditions, while MCs showed significantly shorter nondecision times in the speed compared to accuracy and neutral conditions (figure 13.6).

**Table 13.5 Experiment 5: Lexical Decision. Mean and standard deviation for best-fitting diffusion model parameters by group and condition.**

| | | PWA | | MC | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Conditions | Mean | sd | Mean | sd | *t* | est.df | *p* value |
| $z_r$ | Neutral | 0.492 | 0.057 | 0.531 | 0.055 | 2.261 | 39.656 | 0.029 |
| . | Accuracy | 0.497 | 0.052 | 0.523 | 0.046 | 1.697 | 38.425 | 0.098 |
| . | Speed | 0.480 | 0.060 | 0.492 | 0.061 | 0.659 | 40.397 | 0.513 |
| $s_{zr}$ | . | 0.189 | 0.268 | 0.167 | 0.220 | -0.284 | 36.828 | 0.778 |
| $a$ | Neutral | 2.623 | 0.659 | 2.032 | 0.750 | -2.751 | 40.992 | 0.009 |
| . | Accuracy | 1.951 | 0.553 | 1.842 | 0.660 | -0.588 | 40.953 | 0.560 |
| . | Speed | 1.715 | 0.541 | 1.385 | 0.498 | -2.068 | 39.039 | 0.045 |
| $t_0$ | Neutral | 0.615 | 0.135 | 0.555 | 0.109 | -1.607 | 36.444 | 0.117 |
| . | Accuracy | 0.624 | 0.130 | 0.522 | 0.060 | -3.199 | 25.839 | 0.004 |
| . | Speed | 0.617 | 0.132 | 0.491 | 0.049 | -4.051 | 23.480 | <0.001 |
| $st_0$ | . | 0.244 | 0.070 | 0.146 | 0.050 | -5.190 | 33.910 | <0.001 |
| $v$ | Neutral: HF | 3.478 | 1.745 | 5.394 | 1.683 | 3.653 | 39.723 | 0.001 |
| . | Neutral: LF | 1.591 | 0.959 | 2.676 | 0.880 | 3.844 | 38.969 | <0.001 |
| . | Neutral: NWhigh | -2.024 | 1.027 | -3.521 | 0.913 | -5.018 | 38.424 | <0.001 |
| . | Neutral: NWlow | -2.071 | 1.071 | -3.392 | 0.845 | -4.442 | 36.027 | <0.001 |
| . | Accuracy: HF | 3.656 | 1.374 | 5.134 | 1.288 | 3.623 | 39.315 | 0.001 |
| . | Accuracy: LF | 1.871 | 1.042 | 3.226 | 1.034 | 4.269 | 40.081 | <0.001 |
| . | Accuracy: NWhigh | -2.450 | 1.197 | -3.715 | 0.782 | -4.038 | 31.917 | <0.001 |
| . | Accuracy: NWlow | -2.181 | 1.100 | -3.608 | 0.755 | -4.888 | 32.986 | <0.001 |
| . | Speed: HF | 3.527 | 1.313 | 5.606 | 1.676 | 4.556 | 40.595 | <0.001 |
| . | Speed: LF | 1.831 | 0.977 | 3.036 | 1.200 | 3.628 | 40.842 | 0.001 |
| . | Speed: NWhigh | -2.023 | 1.054 | -3.409 | 1.184 | -4.063 | 40.971 | <0.001 |
| . | Speed: NWlow | -1.980 | 0.885 | -3.498 | -1.113 | -4.979 | 40.706 | <0.001 |
| $s_v$ | . | 1.174 | -0.577 | 1.159 | -0.743 | -0.078 | 40.531 | 0.938 |
| $p$ | . | 0.150 | -0.169 | 0.204 | -0.272 | 0.805 | 37.343 | 0.426 |

Note: Group performance compared by parameter via Welch's Two Sample t-test.

**Figure 13.5. Experiment 5: Lexical Decision. Boundary separation by group and task instruction.**

Error bars represent ± 1 standard deviation.

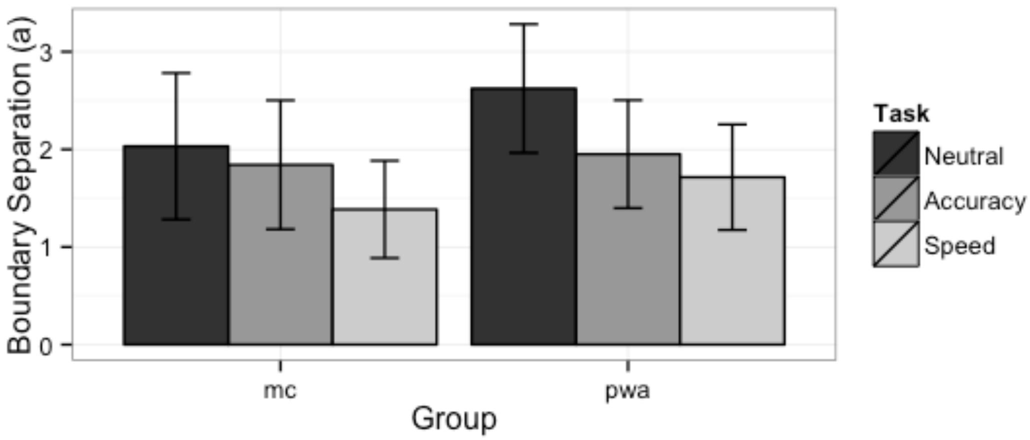
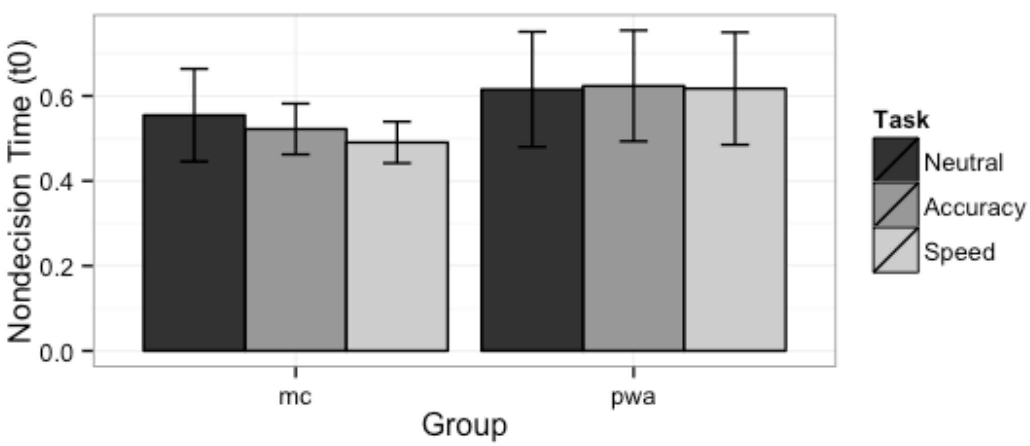



**Figure 13.6. Experiment 5: Lexical Decision. Nondecision time by group and task instruction.**

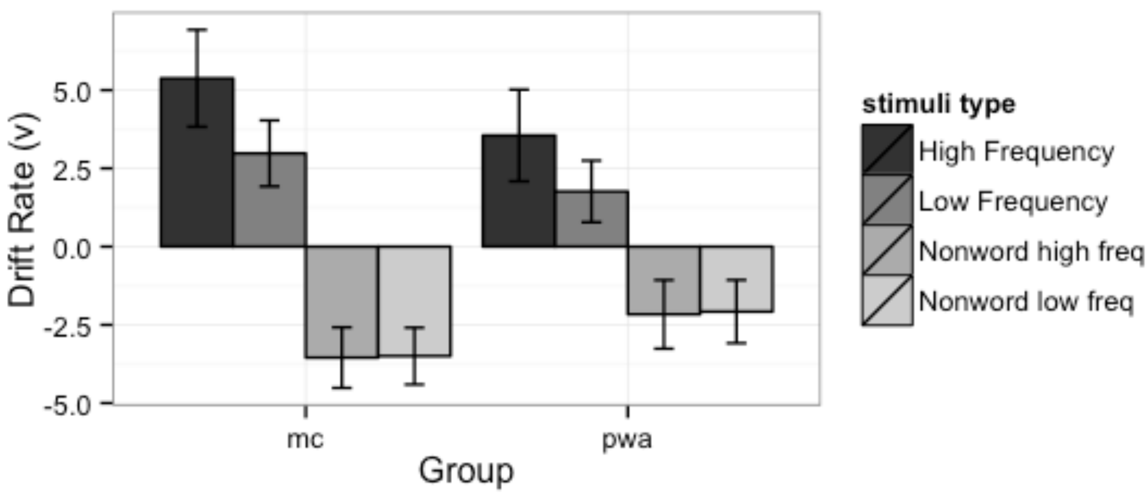
Error bars represent ± 1 standard deviation.




For *v*, there was also a significant interaction between group and stimuli type, $F(3, 123) = 29.386$, $p < .001$, $\eta_p^2$ =.0393. Post-hoc pairwise comparisons revealed that PWA presented with shallower drift rates across stimuli types, and that neither group showed sensitivity to differences in nonword types. In addition, PWA showed a significantly smaller difference between high and low frequency words (figure 13.7). These models also replicated general expected effects of word frequency on drift rate across groups, with high frequency words associated with higher drift rates than low frequency words (*p* < 0.001).

**Figure 13.7. Experiment 5: Lexical Decision. Drift rate by group and stimuli type.**

Error bars represent ± 1 standard deviation.




## 13.4. Discussion

This experiment looked at the ability of PWA and matched controls to perform a lexical decision task with varying task demands focusing on neutral, accurate, or speeded performance. The ability to adapt to varying task constraints was conceptualized as an aspect of cognitive control, while the processing of lexical information and sensitivity to frequency effects was conceptualized as relying primarily on lower-level, relatively automatic lexical processes. It was predicted that that PWA would possess deficits of both types, and that these deficits would be demonstrated in the current experiment.

These hypotheses were largely confirmed in analyses of the empirical response accuracy and response time data, in which PWA showed impaired adaption to speed/accuracy demands with smaller differences between these conditions, and impaired lexical processing based on overall slowed processing and reduced accuracy across stimuli types in this task. The diffusion model was applied to these data in order to gain a more detailed understanding regarding the locus of these impairments.

Although the diffusion model has been applied to PWA in one previous instance (Ratcliff et al, 2004), the current experiment is the first instance in which it has been applied to data from an appropriately powered design that allowed for the modeling of individual participant data and in which PWA were compared to matched controls. In this context, the diffusion model was shown fit the data well for individuals from both groups.

It was predicted that PWA deficits in lexical processing would appear on drift rates ($v$), which was supported by the current results, as PWA showed worse drift rates across conditions. In addition, there was an interaction between group and stimuli type on drift rate, in which PWA presented with less of a drift rate difference between high and low frequency words. This can be interpreted as disproportionately inefficient information extraction for high frequency words.

Although it was also predicted that a control deficit in task adaption for PWA would appear as a reduced difference between boundary separation widths ($a$) in accuracy and speed-focused contexts, they did not show the predicted effect between speed and accuracy conditions. However, PWA set significantly more conservative decision boundaries in the initial neutral condition. While not predicted, this suggests that PWA may set maladaptively conservative response thresholds in linguistic tasks, but that they also appear to be responsive to shifts in task set and the presence of feedback given their subsequent performance on the speed and accuracy conditions.

Although PWA did not demonstrate the predicted task adaption deficits in boundary separation, they did show this pattern on nondecision times ($t_0$): while MCs were able to significantly reduce their $t_0$ times in the speed-focused compared to accuracy condition, PWA showed no differences in $t_0$ across task conditions. Although effects of speed pressure appearing on nondecision times were not initially considered within the diffusion model (for discussion, see Ratcliff an McKoon, 2008), relevant findings have previously been reported by Rinkenauer et al. (2004): In a series of three experiments, one of which employed lexical decision, they manipulated speed demands while measuring specific EEG lateralized readiness potentials (i.e., measures sensitive to response preparation before and after hand activation) in attempt to localize the processing stage of speed pressure effects. They found decreased readiness potential intervals both before and after hand-specific response activation, indicating that speed pressure affects both motor and premotor stages. They also used a simulation study to rule out the possibility that early effects were showing up downstream via a cascade-like processing architecture; in such a model, early and late effects would have had to be directly proportionate, and this was not found across their experiments.

Borrowing this perspective, the current the pattern of results supports the conclusion that the task adaption deficits observed behaviorally in PWA accuracy and response times were largely due to difficulty exerting control to modify motor output performance, and not to abnormal boundary threshold setting. However, Ratcliff et al. (2004) also reported abnormally large nondecision times in their PWA participants, and they claimed that this could reflect differences in *early* encoding related to delayed lexical access. One limitation of the nondecision parameter is that on its own, it does not offer any information about the time-course of associated effects, only that they occur outside the scope of the decision process.

On a final note, the fact that PWA are often shown to present with high processing variability (Hula and McNeil, 2008) also led to the prediction that they would show higher between-trial variability in drift rates, based on the premise that high variability in the efficiency of information extraction could be an explanation for this finding. This result was not found. Instead, PWA were shown to have greater variability in nondecision times, $st_0$. Again, this points to a locus of processing impairment at the stages of very early encoding and/or response execution, and not at the stage of information extraction for the purposes of decision making.

# CHAPTER FOURTEEN

# Experiment 6: Numerosity Judgment with Varying Speed and Accuracy Instructions

## 14.1. Methods and Procedure for Experiment 6

### *14.1.1. Materials and Design*

In Experiment 6, participants were required to make a numerosity judgment (whether a number of presented asterisks was greater or less than 50) within the context of different instruction and feedback task demands (neutral vs. speed-focused vs. accuracy-focused), based on experiment 2 of Ratcliff et al. (2010). Apart from the classification and stimuli, all other aspects of this experiment were matched as closely as possible to experiment 5.

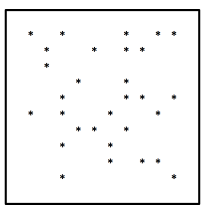
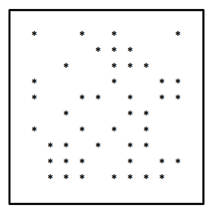
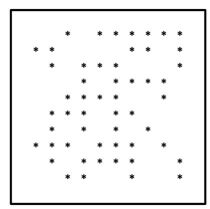
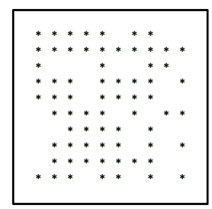
Stimuli were based on those from Ratcliff et al. (2010). Each stimulus consisted of a number of asterisks (from 30 to 49 and from 51 to 70) appearing randomly within a 10 x 10 grind on the computer screen. They were grouped into 4 categories based on their distance from the “low” vs. “high” response threshold of 50 asterisks. Stimuli closer to this threshold were more difficult to classify, so stimuli in the 40–49 and 51–60 asterisk ranges were categorized as hard, while those in the 30–39 and 61–70 range were classified as easy (figure 14.1).

For the current experiment, 360 stimuli (10 for each possible number of asterisks) were randomly pre-generated from each of the four categories using Visual Basic in

Microsoft Excel, for a total of 1440 experimental stimuli. A separate list of 288 practice stimuli were also generated in this manner.

**Figure 14.1. Four representative stimuli from experiment 6, based on Starns and Ratcliff (2010).**

Classification of a stimuli as “high” or “low” based on a threshold of 50 asterisks.

| | | | |
|---|---|---|---|
|  |  |  |  |
| *Easy "Low" Response (30–39)* | *Hard "Low" Response (40–49)* | *Hard "High" Response (51–60)* | *Easy "High" Response (61–70)* |

Overall, Experiment 6 employed a 3x4x2 mixed factorial design, with task contexts (neutral, speed-focused, accuracy-focused) and stimuli type (Low Easy, Low Hard, High Easy, High Hard) as within-subject factors, and group (PWA vs. MC) as a between-subject factor. The ability to adapt and respond to task demands was assessed by looking at performance differences between task contexts, while the ability to process low-level numerosity information was assessed by looking at performance differences between stimulus types.

### *14.1.2. Procedure*

For each participant, stimuli were presented in a total of 15 experimental blocks of 96 trials each. Each block contained 24 stimuli of each type (Low Easy, Low Hard, High Easy, High Hard). Each participant was given the same block order, with trials randomized within each block. The first 5 blocks were presented under ‘neutral’ task instructions stressing both speed and accuracy, while the remaining 10 blocks alternated between instructions stressing speed and instructions stressing accuracy. A short break was offered between each block.

Each trial was preceded by a 150 ms pre-trial interval, and stimuli stayed on the screen until the participant made a response, either by pressing the “left” keyboard key to indicate a “low” response or the “right” keyboard key to indicate a “high” response. In accuracy-focused blocks, the word “INCORRECT” appeared in blue font for 800ms following an error response, while in speed-focused blocks, the words “RESPOND FASTER” appeared in blue font for 800ms following a slow response. This speed feedback threshold was determined for each participant by calculating their 70$^{th}$ quantile for response times in the initial neutral condition blocks.

Each condition was preceded by a set of written instructions that were read to each participant. On neutral blocks, participants were asked to respond both as quickly and as accurately as possible. On accuracy blocks, participants were asked to respond as accurately as possible. On speed blocks, participants were asked to respond as quickly as possible while still classifying the stimuli. Participants received 96 trials of practice for each condition prior to encountering it for the first time. A short break was offered between each block, and participants were provided again with task instructions before beginning the subsequent block.

## 14.2. Statistical and Modeling Techniques

Statistical and modeling techniques followed those used in experiment 5.

## 14.3. Results

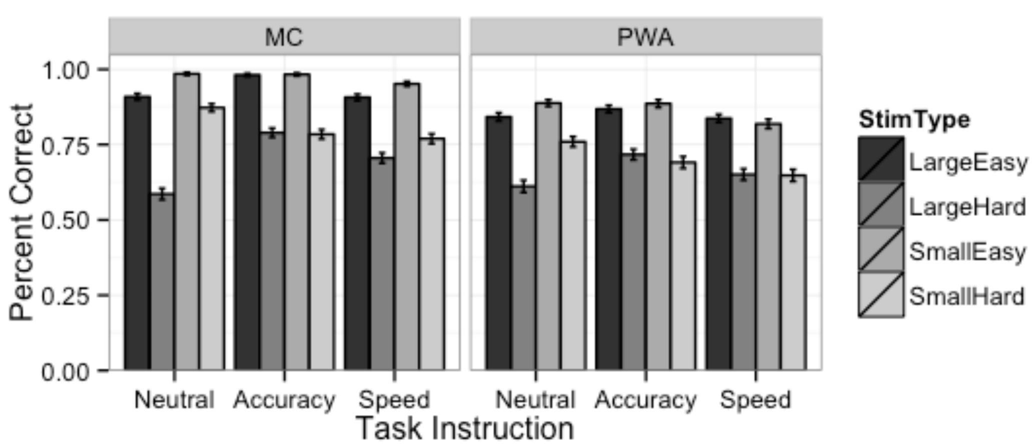
Analyses were conducted on the full set of 20 PWA and 23 MCs.

### *14.3.1. Accuracy*

Mean accuracy rates by group, stimuli type, and task are presented in figure 14.1. Accuracy data were evaluated between groups via mixed-effect logistic regression in separate 2-way interaction models, looking at the interaction between group and stimuli type, and at the interaction between group and task (table 14.2).

**Figure 14.2. Experiment 6: Numerosity Judgment. Accuracy by group, task, and stimulus type.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).



Model results revealed a significant 2-way interaction between task and group, such that while PWA performed worse than controls overall, they showed significantly less differences between accuracy and neutral conditions (PWA mean response accuracy 79% for the accurate condition and 78% for neutral condition; MC mean response accuracy 88% for the accurate condition and 84% for neutral condition; $p < 0.001$), less differences between accuracy and speed conditions (PWA 79% vs. 74%; MC 88% vs. 83%; $p = 0.007$), and greater differences between neutral and speed conditions (PWA 78% vs. 74%; MC 84% vs. 83%; $p < 0.001$).

In contrast to experiment 5, there was a significant interaction between group and stimuli type. PWA performed worse across conditions overall, and they performed disproportionately worse than MCs on both easy conditions compared to hard conditions (mean accuracy on High Easy 85% for PWA and 93% for MCs; High Hard 66% for PWA and 70% for MCs; on Low Easy 86% for PWA and 97% for MCs; on Low Hard 70% for PWA and 81% for MCs; $p$s $\leq 0.001$).

**Table 14.1. Experiment 6: Numerosity Judgment, primary analyses of response accuracy. Fixed effect estimates from logistic mixed-effect models of response accuracy on group, task, and stimuli type.**

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| **14.1.1 Group x Task** | | | | |
| (Intercept) | 2.45 | 0.13 | 19.23 | <0.001 |
| TaskNeutral | -0.42 | 0.08 | -5.55 | <0.001 |
| TaskSpeed | -0.56 | 0.08 | -7.40 | <0.001 |
| Group | -0.76 | 0.17 | -4.41 | <0.001 |
| TaskNeutral: Group | 0.33 | 0.06 | 5.66 | <0.001 |
| TaskSpeed: Group | 0.15 | 0.06 | 2.68 | 0.007 |
| *AIC: 51002* | | | | |
| | | | | |
| **14.1.2 Group x Stimuli type** | | | | |
| (Intercept) | 2.83 | 0.13 | 22.47 | <0.001 |
| StimTypeHighHard | -1.90 | 0.07 | -28.03 | <0.001 |
| StimTypeLowEasy | 1.00 | 0.09 | 10.80 | <0.001 |
| StimTypeLowHard | -1.23 | 0.07 | -17.77 | <0.001 |
| Group | -0.86 | 0.18 | -4.91 | <0.001 |
| StimTypeHighHard: Group | 0.70 | 0.07 | 10.46 | <0.001 |
| StimTypeLowEasy: Group | -0.85 | 0.09 | -9.05 | <0.001 |
| StimTypeLowHard: Group | 0.24 | 0.07 | 3.47 | 0.001 |
| *AIC: 49622* | | | | |

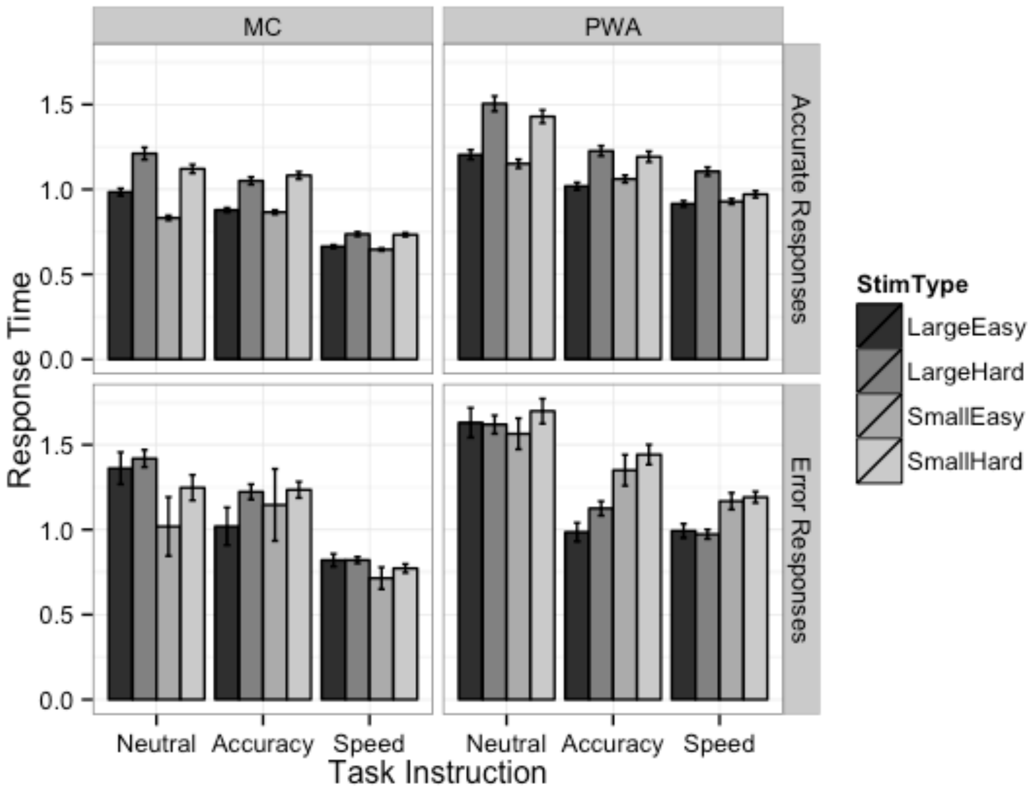
Note: Reference value for task = accuracy condition; reference value for stimuli type= "High Easy". Initial version of models obtained convergence warnings and models with simplified random effects structures with random intercepts only are presented.

*14.3.2. Response times*

Visual inspection of raw response times via quantile-quantile plots by subject revealed a small number of extreme outliers and a general rightward skew of the response distributions. Therefore, cutoffs were set with responses below 200 ms and above 5000 ms dropped prior to analysis (less than 1.3% of trials). Mean raw response times rates by group, condition, and response accuracy are presented in figure 14.3.

**Figure 14.3. Experiment 6: Numerosity Judgment. Response time (s) by group, response accuracy, task, and stimuli type.**

Error bars represent 95% confidence intervals calculated using normalized within-subjects standard errors (Morey, 2008).




Log-transformed response times were analyzed as in experiment 5 (table 14.3). Model results revealed a significant 2-way interaction between task and group, where PWA took marginally longer than controls on the neutral compared to accurate condition ($p = 0.087$), and showed less of a difference in the speed vs. accuracy conditions compared to controls ($p = 0.007$). PWA were slower overall across stimuli types, and there was evidence for a marginally-significant interaction between group and stimuli type, such that MCs were faster on Low Easy compared to High Easy, but PWA did not show this difference ($p = 0.056$).

**Table 14.2. Experiment 6: Numerosity Judgment, primary analyses of response time. Fixed effect estimates from linear mixed-effect models of log response time on group, task, and stimuli type.**

| | Estimate | Std. Error | Est. df | t value | Pr (>\|t\|) |
|---|---|---|---|---|---|
| **14.2.1 Group x Task** | | | | | |
| (Intercept) | -0.11 | 0.06 | 41.56 | -1.92 | 0.062 |
| TaskNeutral | 0.05 | 0.05 | 42.60 | 0.97 | 0.338 |
| TaskSpeed | -0.29 | 0.04 | 43.20 | -7.20 | <0.001 |
| Group | 0.12 | 0.08 | 40.99 | 1.49 | 0.145 |
| TaskNeutral: Group | 0.12 | 0.07 | 41.00 | 1.76 | 0.087 |
| TaskSpeed: Group | 0.17 | 0.06 | 41.00 | 2.85 | 0.007 |
| *AIC:* 46702 | | | | | |
| **14.2.2 Group x Stimuli type** | | | | | |
| (Intercept) | -0.24 | 0.05 | 43.22 | -5.13 | <0.001 |
| StimTypeHighHard | 0.16 | 0.02 | 71.39 | 7.26 | <0.001 |
| StimTypeLowEasy | -0.07 | 0.03 | 53.40 | -2.34 | 0.023 |
| StimTypeLowHard | 0.12 | 0.04 | 49.81 | 3.49 | 0.001 |
| Group | 0.19 | 0.07 | 40.99 | 2.83 | 0.007 |
| StimTypeHighHard: Group | -0.01 | 0.03 | 40.97 | -0.31 | 0.760 |
| StimTypeLowEasy: Group | 0.08 | 0.04 | 41.02 | 1.96 | 0.056 |
| StimTypeLowHard: Group | 0.02 | 0.05 | 41.00 | 0.50 | 0.619 |

Note: Reference value for task = accuracy condition; reference value for stimuli type= “High Easy”.

### *14.3.3. Diffusion Models*

Diffusion models were fit individually to each participant by entering their response time distributions for correct and error responses into *fast-dm-30* (Voss et al., 2015), as in experiment 5.

Diffusion model starting point ($z_r$), boundary/threshold separation (a), and nondecision time ($t_0$) were estimated separately by task, while drift rates ($v$) were estimated separately by task and stimuli type. All other parameters were held constant across conditions with the exception of $d$, which was not included in current models.

Model adequacy was evaluated as in experiment 5 by plotting predicted against empirical response time quantiles for each condition in each participant at the 25, 50, and 75 quantiles for correct and error responses. Results are plotted by group in figures 14.4 and 14.5. These plots showed good fits for both groups across quantiles for both correct and error responses. In contrast, experiment 5 showed much worse fits for error response distributions. Improved fits in the current experiment are likely due to lower accuracy rates overall, allowing a greater number of error responses to contribute to parameter estimation.

**Figure 14.4. Experiment 6: Numerosity Judgment. Empirical versus predicted response times for correct and error responses across all conditions for PWA group.**

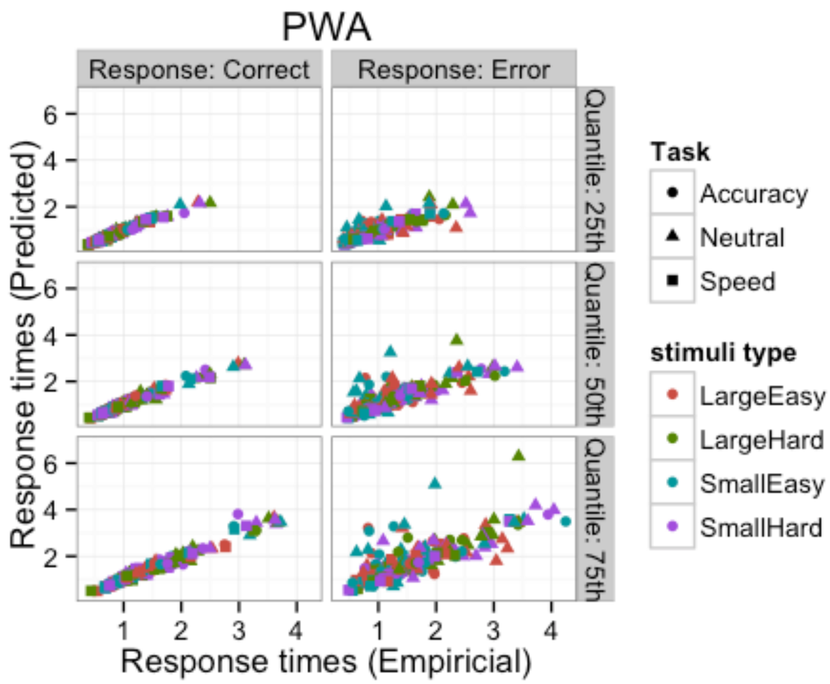



**Figure 14.5. Experiment 6: Numerosity Judgment. Empirical versus predicted response times for correct and error responses across all conditions for MC group.**

Mean parameter estimates are presented in table 14.3. Welch's Two Sample *t*-tests run separately by parameter and evaluated for significance based on an uncorrected alpha of 0.05 (table 14.4) showed that groups differed in the following contexts: the neutral task condition on $a$ and $t_0$, $st_0$, and for the Low Easy conditions on $v$ ($p$s $< 0.01$ for speed and accuracy contexts; marginal at $p = 0.076$ for neutral context). Groups did not differ in terms of $z_r$, $s_{zr}$, $s_v$, or $p$ ($p$s $> 0.05$).

Group differences were further evaluated for the parameters that were allowed to vary between conditions ($zr$, $a$, $t_0$, and $v$) via separate two-way repeated-measures ANOVAs crossing task and group for $zr$ and $a$, and crossing stimuli type and group for $v$ (collapsing across task). There were no interactions between group and task for $z_r$, $F(2, 82) = 0.295$, $p = .745$, $\eta_p^2 = .002$, or for $a$, $F(2, 82) = 0.477$, $p = .622$, $\eta_p^2 = .005$, although there was a main effect of group for $a$, with PWA setting wider boundaries overall $F(1, 41) = 6.936$, $p = .012$, $\eta_p^2 = .091$.

For $t_0$, there was a significant interaction between group and task, $F(2, 82) = 4.337$, $p = .016$, $\eta_p^2 = .025$. Post-hoc pairwise comparisons revealed that nondecision times remained constant and marginally larger for PWA across task conditions ($p = 0.08$), while MCs showed significantly shorter nondecision times in the speed compared to accuracy and in the neutral compared to accuracy conditions (figure 14.6).

For $v$, there was also a significant interaction between group and stimuli type, $F(3, 123) = 6.113$, $p = .001$, $\eta_p^2 = .094$. Post-hoc pairwise comparisons revealed that while there were no group differences overall, PWA showed a significantly smaller difference between Low Easy and Low Hard responses, but not between High Easy and High Hard responses (figure 14.7). These models also replicated general expected effects of discrimination difficulty on drift rate across groups, with the “hard” stimuli categories shower shallower drift rates than the “easier” stimuli categories (*ps* $< 0.001$).

**Table 14.3. Experiment 6: Numerosity Judgment. Mean and standard deviation for best-fitting diffusion model parameters by group and condition.**

| | | PWA | | MC | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Conditions | Mean | sd | Mean | sd | $t$ | est.df | $p$ value |
| $z_r$ | Neutral | 0.511 | 0.050 | 0.517 | 0.061 | 0.337 | 40.851 | 0.738 |
| . | Accuracy | 0.513 | 0.056 | 0.516 | 0.053 | 0.172 | 39.419 | 0.864 |
| . | Speed | 0.523 | 0.078 | 0.517 | 0.071 | -0.294 | 38.857 | 0.770 |
| $s_{zr}$ | . | 0.301 | 0.352 | 0.162 | 0.231 | -1.511 | 32.019 | 0.141 |
| $a$ | Neutral | 2.788 | 0.921 | 2.377 | 0.813 | -1.540 | 38.285 | 0.132 |
| . | Accuracy | 2.188 | 0.661 | 1.886 | 0.630 | -1.525 | 39.562 | 0.135 |
| . | Speed | 1.727 | 0.423 | 1.207 | 0.353 | -4.335 | 37.166 | <0.001 |
| $t_0$ | Neutral | 0.586 | 0.220 | 0.474 | 0.071 | -2.179 | 22.439 | 0.040 |
| . | Accuracy | 0.561 | 0.129 | 0.553 | 0.115 | -0.212 | 38.370 | 0.834 |
| . | Speed | 0.572 | 0.199 | 0.486 | 0.060 | -1.851 | 22.012 | 0.078 |
| $st_0$ | . | 0.351 | 0.229 | 0.180 | 0.080 | -3.175 | 23.002 | 0.004 |
| $v$ | Neutral: HighEasy | 2.347 | 1.837 | 2.618 | 1.268 | 0.556 | 33.104 | 0.582 |
| . | Neutral: HighHard | 0.545 | 1.040 | 0.518 | 1.082 | -0.082 | 40.564 | 0.935 |
| . | Neutral: LowEasy | -3.431 | 2.590 | -4.668 | 1.659 | -1.833 | 31.512 | 0.076 |
| . | Neutral: LowHard | -1.506 | 1.415 | -2.097 | 1.079 | -1.521 | 35.278 | 0.137 |
| . | Accuracy: HighEasy | 2.678 | 1.800 | 3.665 | 1.419 | 1.975 | 35.994 | 0.056 |
| . | Accuracy: HighHard | 1.074 | 1.087 | 1.498 | 0.792 | 1.443 | 34.289 | 0.158 |
| . | Accuracy: LowEasy | -2.614 | 1.655 | -4.067 | 1.495 | -3.004 | 38.703 | 0.005 |
| . | Accuracy: LowHard | -1.188 | 1.093 | -1.464 | 0.653 | -0.985 | 30.098 | 0.333 |
| . | Speed: HighEasy | 2.506 | 2.067 | 3.272 | 1.460 | 1.383 | 33.598 | 0.176 |
| . | Speed: HighHard | 0.643 | 1.109 | 1.117 | 1.101 | 1.403 | 40.088 | 0.168 |
| . | Speed: LowEasy | -2.739 | 2.272 | -4.474 | 1.319 | -3.003 | 29.584 | 0.005 |
| . | Speed: LowHard | -1.205 | 1.540 | -1.835 | 1.142 | -1.505 | 34.663 | 0.141 |
| $s_v$ | . | 1.594 | 1.061 | 1.503 | 0.663 | -0.331 | 31.007 | 0.743 |
| $p$ | . | 0.107 | 0.102 | 0.123 | 0.102 | 0.539 | 40.066 | 0.593 |

Note: group performance by parameter compared via Welch's Two Sample t-test.

**Figure 14.6. Experiment 6: Numerosity Judgment. Boundary separation by group and task instruction.**

Error bars represent ± 1 standard deviation.

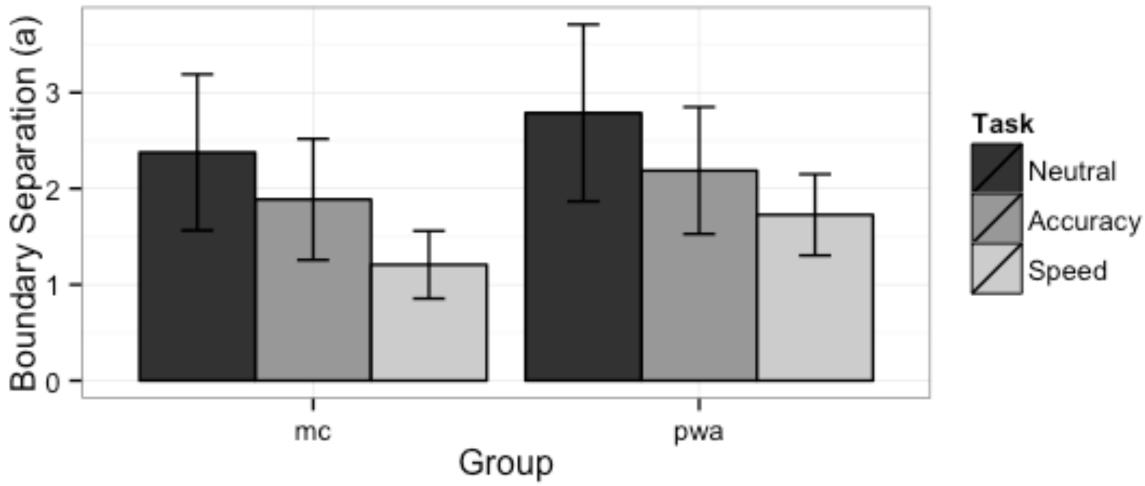



**Figure 14.7. Experiment 6: Numerosity Judgment. Nondecision time by group and task instruction.**

Error bars represent ± 1 standard deviation.

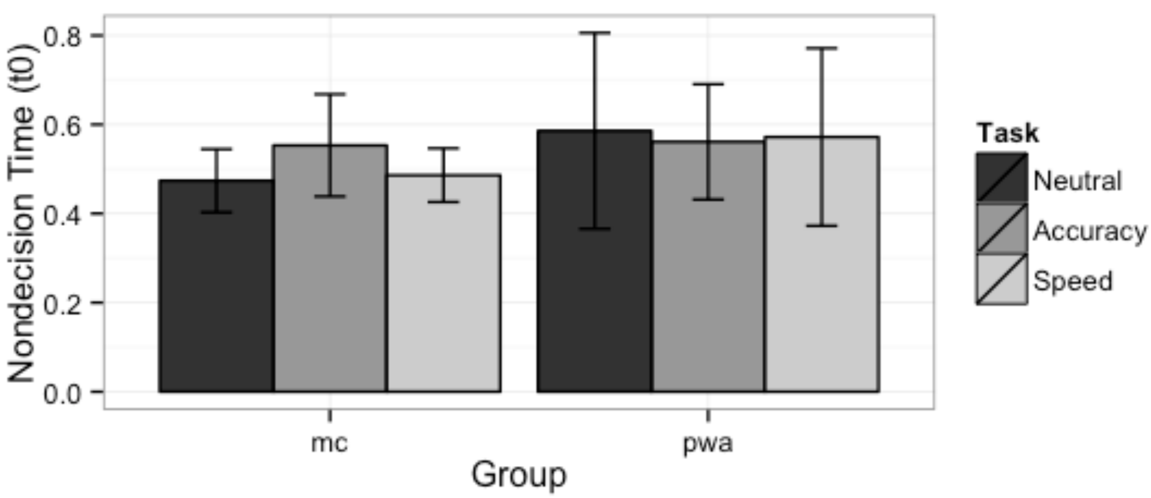
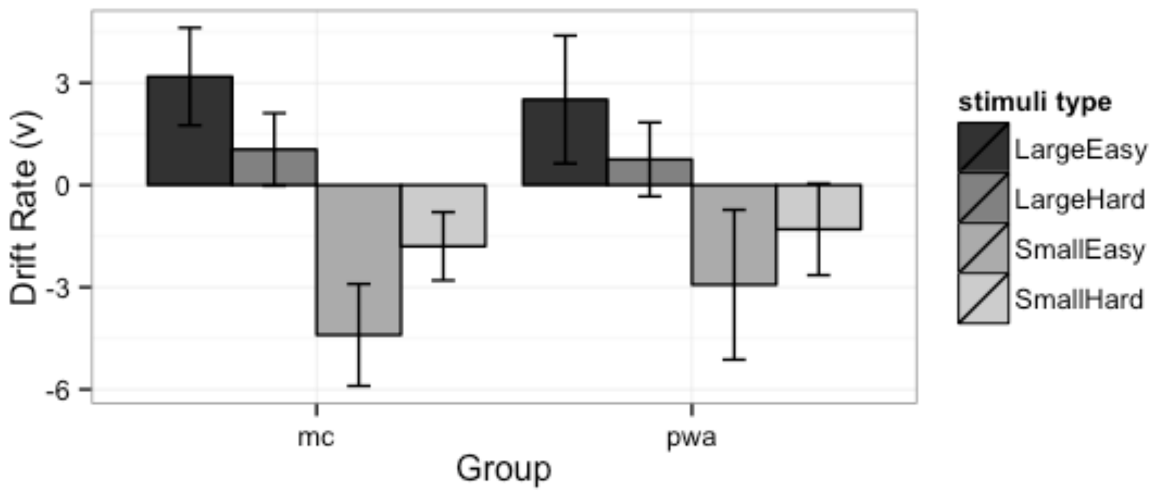


**Figure 14.8. Experiment 6: Numerosity Judgment. Drift rate by group and stimuli type.**

Error bars represent ± 1 standard deviation.




## 14.4. Discussion

This experiment looked at the ability of PWA and matched controls to perform a numerosity judgment task with varying task demands focusing on neutral, accurate, or speeded performance. The ability to adapt to varying task constraints was conceptualized as an aspect of cognitive control, while the processing of numeracy information was conceptualized as a lower level, relatively automatic, domain-specific visuospatial process. It was predicted that PWA would present with deficits of the first type but not the second in this experiment.

As in experiment 5, the prediction that PWA would demonstrate impaired cognitive control in terms of speed vs. accuracy task adaption was confirmed in the empirical data: PWA demonstrated less shifts in response accuracy and response times between conditions compared to MCs. It was predicted that this control deficit in task adaption would appear in the diffusion model as a reduced difference between boundary separation widths in accuracy and speed focused contexts. Although PWA set more conservative decision boundaries overall, they did not show the predicted effect between speed and accuracy conditions. However, as in experiment 5, they again showed this effect on nondecision times ($t_0$); while PWA showed no significant differences in $t_0$, MCs showed significantly shorter times in the speed-focused condition. These results are consistent with those from experiment 5, and support the conclusion that the task adaption deficits observed behaviorally in PWA accuracy and response times were largely due to difficulty exerting control to modify motor output performance, and not to abnormal boundary threshold setting. The fact that this pattern occurred across experiments suggests that this is a domain-general deficit, and argues against the claims of Ratcliff et al. (2004), in which they attributed their abnormal nondecision times to delayed lexical access.

It was also predicted that PWA and MC would not show differences in numerosity judgments based on stimuli discrimination difficulty, given the low level and nonlinguistic nature of this task. However, PWA showed a pattern of disproportionate difficulty on the easier stimuli conditions, for both High and Low stimuli for response accuracy, and on low stimuli for response times and drift rates. Given similar findings in experiment 5 for high vs. low-frequency words, it appears that PWA are disproportionately inefficient at extracting information from relatively easy sources across domains. While this seems to be a general difficulty, it should be noted that there were some differences in drift rate across tasks: PWA demonstrated lexical access deficits in that they performed worse across conditions in experiment 5. In contrast, their performance was similar to MCs on harder stimuli in the current experiment, which indicates that a the general deficits they display in efficient evidence accumulation across tasks does cannot on its own account for the lexical processing deficits they experience.

# CHAPTER FIFTEEN

## Domain Specificity in Task Adaption for Speed-Accuracy Trade-offs and their Relation to Executive Attention

The last two chapters reported experiments where the diffusion model was used to investigate task adaption in varying speed and accuracy-focused contexts. Experiment 5 used lexical decision, while experiment 6 used a numerosity judgment task. In both, aspects of control were manipulated by varying task instructions (neutral, speed emphasis, accuracy emphasis), while lower-level aspects of lexical processing were manipulated by varying word frequency or numerical discrimination difficulty.

Analyses focusing on each experiment individually found generally consistent results: in both experiments, group by task interactions were found on nondecision times, characterized by an inability of PWA to reduce nondecision times in the presence of speed focus. Neither experiment found group by task interactions on boundary separation. Both experiments also found group by stimulus type interactions in which PWA showed disproportionately reduced processing efficiency on easy stimuli. The current chapter further evaluates these results via direct statistical comparison, and also examines the relationships between diffusion model performance and the construct of executive attention.

## 15.1. Results

### *15.1.1. Diffusion model comparisons between experiments 5 and 6*

Correlations for diffusion model parameters between experiments 5 and 6 are reported by group in table 15.1. One often-discussed strength of the diffusion model is that a given model parameter tends to correlate fairly well across experiments, but correlate poorly with other parameters within the same experiment (e.g., Ratcliff & McKoon, 2008). When combined with the fact that model parameters tend to be differentially sensitive to various experimental manipulations (e.g., stimuli proportions on response bias, word frequency effects on drift rates), this is interpreted to mean that model parameters truly reflect basic aspects of the decision process.

As an example of cross-experiment correlation relevant to the current work, Ratcliff et al. (2010) reported correlations between a lexical decision and numerosity in a sample of old and young participants at $r$ =.33 for boundary width, .47 for nondecision time, and .47 for drift rate. Averaging across task type by group, correlations in the current experiment are roughly in the same range for boundary width (MC $r$ = .37; PWA $r$ = .55) and non-decision time for both groups (MC $r$ = .24; PWA $r$ = .63), but not for drift rate (MC $r$ = .06; PWA $r$ = .07). Although it was predicted that drift rates would differ across experiments for PWA given the differences in lexical processing involved, this was *not* predicted for MCs, and the source of this difference is unclear. It may be related to shifts in speed and accuracy focus, as the drift rate correlations for MCs in the neutral condition had a more expected average correlation ($r$ = .47).

**Table 15.1. Correlations between diffusion parameters for experiment 5: Lexical Decision, and Experiment 6: Numerosity Judgment, separately by group.**

| Parameter | Condition | PWA | MC |
|---|---|---|---|
| zr | Neutral | -0.01 | 0.35 |
| . | Accuracy | 0.14 | 0.04 |
| . | Speed | 0.08 | 0.19 |
| szr | . | 0.30 | 0.47 |
| a | Neutral | 0.69 | 0.11 |
| . | Accuracy | 0.50 | 0.62 |
| . | Speed | 0.47 | 0.38 |
| t0 | Neutral | 0.62 | 0.42 |
| . | Accuracy | 0.63 | 0.11 |
| . | Speed | 0.65 | 0.19 |
| st0 | . | 0.49 | -0.09 |
| v | Neutral: HighEasy/ HF | 0.16 | 0.53 |
| . | Neutral: HighHard/ LF | -0.02 | 0.41 |
| . | Accuracy: HighEasy/ HF | 0.15 | -0.18 |
| . | Accuracy: HighHard/ LF | -0.08 | 0.15 |
| . | Speed: HighEasy/ HF | 0.08 | -0.26 |
| . | Speed: HighHard/ LF | 0.14 | -0.32 |
| sv | . | 0.51 | -0.20 |
| p | . | 0.06 | 0.52 |

Note: correlations between experiments for lower boundary drift rate responses not reported due to qualitative differences in stimuli.

Diffusion model differences were evaluated between experiments for the parameters *v*, *a*, and $t_0$ in a set of 3-way repeated measures ANOVAs. Analysis of *v* crossed stimulus condition for the upper bound responses (HF words/Large Easy numerosity vs. LF words /Large Hard numerosity), experiment domain (lexical decision vs. numerosity), and group, while analyses for *a* and $t_0$ crossed task condition, experiment domain, and group (table 15.2).

For *v*, there was no 3-way interaction ($p = 0.54$). However, there were main effects of group, condition, and domain ($ps < 0.001$). There were also two-way interactions between group and stimulus condition, such that PWA showed less of a difference between easy and hard stimuli across domain types ($p = 0.01$), and between group and domain, such that MC presented with higher drift rates in lexical decision compared to numerosity, but PWA did not differ between domains.

For *a*, there were main effects of group, with PWA setting more conservative criteria overall, and of task ($p$s $< 0.01$), but no effects of domain, and no interactions involving group ($p$s $> 0.05$). However, there was a two-way interactions between task and domain, and post-hoc pairwise testing revealed a larger difference between speed and accuracy focused conditions in numerosity comparison to lexical decision that was marginally significant ($p = 0.08$). Although the separate experiment analyses reported a significant interaction between group and task in lexical decision and no such relationship in numerosity judgment, the difference between these does not appear to be significant when tested directly, and boundary widths in the numerosity task show the same general trends without reaching significance.

For $t_0$, there was a 3-way interaction between group, task, and domain ($p = 0.002$). Post-hoc comparisons of the constituent 2-way interactions revealed that this interaction was driven by differences in the neutral condition for MCs between experiments, who showed no differences between neutral and accuracy focused conditions in lexical decision, but were faster in neutral compared to accuracy focused conditions in numerosity ($p = 0.018$; figure 15.1). In terms of the 2-way task by group interactions on $t_0$ reported separately in both experiments 5 and 6, the effect was only marginally significant overall in current analysis ($p = 0.076$). However, this was due to MC differences in the neutral condition between experiments washing out group effects; a secondary model looking specifically at group differences in the speed vs. accuracy conditions in a separate ANOVA collapsing across experiment showed the crucial task adaption effect previously reported: $F(1, 41) = 7.067$, $p = .011$, $\eta_p^2 = .02$.

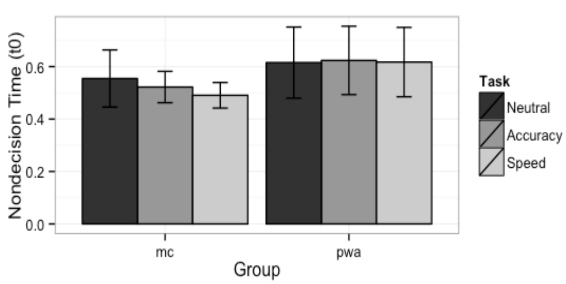
**Table 15.2. ANOVA comparisons of group, domain, and condition for experiments 5 and 6 on drift rate parameters.**

| | DFn | DFd | F | p<.05 | $\eta_p^2$ |
|---|---|---|---|---|---|
| **15.2.1 Drift rate (*v*)** | | | | | |
| Group | 1 | 41 | 15.74 | <0.001* | 0.17 |
| StimType | 1 | 41 | 306.29 | <0.001* | 0.46 |
| Domain | 1 | 41 | 68.85 | <0.001* | 0.33 |
| group: StimType | 1 | 41 | 4.53 | 0.039* | 0.01 |
| group: Domain | 1 | 41 | 7.37 | 0.010* | 0.05 |
| StimType: Domain | 1 | 41 | 0.71 | 0.404 | 0.00 |
| group: StimType: Domain | 1 | 41 | 0.38 | 0.54 | 0.00 |
| **15.2.2 Boundary width (*a*)** | | | | | |
| group | 1 | 41 | 7.42 | 0.009* | 0.08 |
| Task | 2 | 82 | 68.16 | <0.001* | 0.28 |
| Domain | 1 | 41 | 1.59 | 0.215 | 0.01 |
| group: Task | 2 | 82 | 1.80 | 0.173 | 0.01 |
| group: Domain | 1 | 41 | 0.17 | 0.679 | 0.00 |
| Task: Domain | 2 | 82 | 5.45 | 0.006* | 0.01 |
| group: Task: Domain | 2 | 82 | 1.98 | 0.144 | 0.01 |
| **15.2.3 Nondecision time ($t_0$)** | | | | | |
| group | 1 | 41 | 8.52 | 0.006* | 0.10 |
| Task | 2 | 82 | 2.62 | 0.079 | 0.01 |
| Domain | 1 | 41 | 2.55 | 0.118 | 0.02 |
| group: Task | 2 | 82 | 2.65 | 0.076 | 0.01 |
| group: Domain | 1 | 41 | 0.52 | 0.477 | 0.00 |
| Task: Domain | 2 | 82 | 2.84 | 0.064 | 0.01 |
| group: Task: Domain | 2 | 82 | 7.01 | 0.002* | 0.02 |

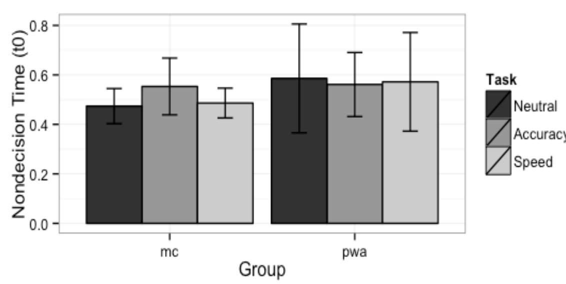
**Figure 15.1. Comparisons of group, domain, and task for experiment 5 (left) and experiment 6 (right) on nondecision times $t_0$.**

Error bars represent ± 1 standard deviation.

*Experiment 5: Lexical Decision*




*Experiment 6: Numerosity Judgment*




*15.1.2. Effects of executive attention on experiments 5 and 6.*

It was predicted that generating and maintaining speed and accuracy priorities in response to varying task constraints required task maintenance, and that any group differences in task adaption would be attributable to differences in this aspect of executive attention. This hypothesis was tested using ANCOVAs focusing on nondecision time performance collapsing across experiments, given the fact that this is where group differences in task adaption were found to occur. ANCOVAs were run testing for the interaction between group and task instruction (speed vs. accuracy) when controlling for individual differences in task maintenance. Task maintenance was measured via the differences scores reported in chapter 12, and two versions of this ANCOVA were evaluated; one that partialed out task maintenance ability based on performance in the SART experiments 1 and 2, and one that partialed out performance on the Stroop experiments 3 and 4. Task maintenance covariates were split in this way for model parsimony, and also due to the notably divergent patterns of impairments between these task types reported in Chapter 12 (PWA who showed impairment in one SART task tended to show impairment on the other, but not on either Stroop task, and vice versa). Neither of these ANCOVAs mediated the task by group interaction on nondecision times ($p$s < 0.01), indicating that group differences in non-decision times we're not due to differences in task maintenance.

Previous work has reported some effects of working memory and fluid intelligence on drift rate (e.g., Ratcliff et al., 2010; Schmiedek et al., 2007). Given group differences in drift rates and the theoretical relationship between executive attention, working memory, and fluid intelligence (Engle and Kane, 2004), the above ANCOVA approach was also employed to determine if these measures mitigated group differences in drift rate as well. Again, two ANCOVAs were run, partialling out SART and Stroop-related task maintenance while testing for the interaction between group and stimuli type on drift rates reported in table 15.2. However, the significant interaction term remained unchanged in both models ($p$s < 0.05), indicating that group differences and drift rate processing were not due to task maintenance deficits.

## 15.2. Discussion

Overall, the direct comparison of diffusion model results from experiments 5 and 6 largely confirmed the findings presented separately in chapters 13 and 14; group by task interactions were found on nondecision times across experiments, characterized by an inability of PWA to reduce nondecision times in the presence of speed focus, which is interpreted as a task adaption deficit. In addition, there was a 3-way interaction between group, task, and domain driven by the fact that MCs showed no differences between neutral and accuracy focused conditions in lexical decision, but were faster in neutral compared to accuracy focused conditions in numerosity. This highlights the fact that in the neutral condition, participants were instructed to respond both as quickly and as accurately as possible: in other words, the condition was "neutral" in that it was balanced between speed and accuracy emphasis, but still had task goals oriented towards both. In the case of MCs, it appears that they interpreted these instructions in such a way as to induce time pressure and speed their nondecision times. The question follows as to why they would respond this way in the numerosity task but not in lexical decision. One possibility is differences in engagement; lexical decision was a very easy task for MCs, while numerosity was more difficult and novel. It is therefore possible that nondecision time speeding effects are affected by level of effort and motivation.

Results in this chapter also confirmed the lack of task adaption differences between groups on boundary separation. Although from an intuitive perspective, it seemed reasonable to expect task maintenance to exert a level of control on this parameter, especially since it is know to be sensitive to conscious and deliberate changes to task set and internal goal states, there is some evidence that boundary setting is in fact relatively resistant to variation: Ratcliff et al. (2015) looked at a series of different numerically-based tasks via diffusion modeling, including numerosity with varying speed instructions, and found that boundary separation values remained correlated *despite* varying instruction focus, concluding that "Subjects may have considerable flexibility in altering their settings, but the adjustments appear to be a function of their base values" (p.133). In their discussion, they conjecture that this relative invariance at the individual might be due to poor accuracy experience in one domain overgeneralizing across domains. If this is true, it could explain why PWA set significant wider boundaries in numerosity judgment based on their experience with lexical performance, even though their drift rates were equivalent to MCs in all but one of the easiest processing conditions in the numerosity task.

Combined analyses of drifts rates also confirmed the individual experiment analyses; PWA had worse drift rates than MCs in lexical decision and disproportionately poor performance in the easiest stimuli conditions across domains. The first of these confirms lexical processing difficulties are present in this population, while the second points to more general information processing concerns that will be considered in the general discussion.

In regards to executive attention measures, there was no indication of mediating effects on the group differences reported for drift rates or nondecision times. Further discussion of these relationships, and the overall role of executive attention in lexical processing tasks of this type will be left for the general discussion.

# CHAPTER SIXTEEN

## General Discussion

The goal of this project was to investigate the relationship between executive attention and specific linguistic and control processes during goal-directed tasks in aphasia. Its central premise was that PWA often possess simultaneous but dissociable impairments in linguistic processes and in the mechanisms that control and efficiently utilize those processes. The motivation for this claim was based on observations that PWA often present with deficits in the online processing of linguistic information, which in some instances has been interpreted as evidence for impaired linguistic operations, but in others has been interpreted as evidence for impaired *control* of language processing due to more general cognitive constraints. Therefore, this project was designed to investigate the role of one general cognitive control model in aphasia, that of Executive Attention (Kane and Engle, 2003), and to test its relation to deficits in lexical processing.

This study tested 20 PWA and 23 MCs on a set of six experiments designed to investigate these relationships: Experiments 1 through 4 were designed to characterize aspects of executive attention in order to identify whether these functions were impaired across semantic and visuospatial domains, and to determine whether these abilities affected controlled language processing. Experiments 1 and 2 tested executive attention and sustained attention using the Sustained Attention to Response (SART) paradigm (Robertson et al., 1997), while experiments 3 and 4 relied on variations on the Stroop paradigm (Stroop, 1935) using word-picture interference and spatial interference.

Experiments 1 and 3 required semantic classifications while experiments 2 and 4 required perceptual/visuospatial classifications.

Specific aim 1 predicted that PWA would show patterns of impaired task maintenance and conflict resolution on these tasks, but that these components of executive attention would differ in terms of domain specificity: task maintenance deficits would present as domain-general across tasks, while conflict resolution deficits would dissociate between processing domains.

Experiments 5 and 6 investigated task adaption to varying speed and accuracy-focused contexts while making lexical or nonlinguistic classifications, and were designed to allow for the application of diffusion modeling. Specific aim 2 claimed that task adaption in these contexts required active task maintenance; therefore, PWA were expected to perform worse than controls as measured on boundary separation (*a*), a parameter of the diffusion model known to be specifically sensitive to this type of task manipulation, and they were expected to show these deficits regardless of task domain. It was also predicted that measures of task maintenance would mediate this interaction effect.

In addition, PWA were also predicted to show lower-level deficits on drift rates for lexical decision but not for numerosity judgment due to lexical processing impairments.

In regards to specific aim 1, group level analyses of experiments 1 through 4 did not provide any evidence in support of conflict resolution deficits for PWA. Clear support for PWA task maintenance deficits was only found in experiment 4, the spatial Stroop task. One rather straightforward conclusion to be gleaned from these results is that executive attention deficits and stroke-induced aphasia clearly dissociate. However, given the widely heterogeneous and generally mildly impaired sample employed in this study, this conclusion is hardly surprising.

Results from the case series analyses provide much stronger supporting evidence for the domain specificity of conflict resolution and for the domain generality of task maintenance: almost without exception, PWA who presented with impairments meeting a strong threshold of evidence showed high correspondence between semantic and perceptual SART tasks, and between semantic and visuospatial Stroop tasks. In contrast, there was not a single instance of conflict resolution deficits appearing in both semantic and visuospatial domains. Overall, this pattern of group and individual analyses support the conclusion that while they are not an intrinsic feature of "aphasia" as broadly defined, executive attention impairments do clearly exist in some portion of this population. In addition, when these deficits do occur, the mixed domain-general and domain-specific presentation pattern supports a model of cognitive control closely in line with the working memory model of Postle (2006). In this model, working memory capacity within a given domain is claimed to be a natural consequence of pairing general attentional resources with any cognitive subsystems specialized in processing specific domain-internal information. However, for these accounts to be fully consistent, they require the additional theoretical claim that these domain-internal processing resources are largely responsible for the implementation of conflict resolution. One plausible conceptualization of conflict resolution in these terms is based on findings from the expertise literature (e.g., Ericsson & Kintsch, 1995), in which domain-specific expertise increases the specificity of encoding and retrieval structures with a consequent reduction in domain-internal interference (e.g., memory for legal vs. non-legal chess moves for chess masters).

This account also offers one potential explanation for why SART and Stroop-based measures of task maintenance did not show a higher level of correspondence in the case series analyses, as they differ completely in regards to the locus of task interference: interference is entirely stimuli-driven and domain-internal for the Stroop tasks, but intrinsically cross-domain in the SART tasks, based on inhibiting motor habituation to a frequently appearing category. With this account, it easy to postulate that cross-domain interference might place qualitatively different demands on task maintenance when compared to within-domain interference.

In addition to the case-level support for the original executive attention claims, group level performance on the executive attention experiments also suggest the presence of an additional control deficit in forming and maintaining efficient stimulus response mappings (Schmiedek et al., 2007). In the experiment 1 and 2 SART tasks, PWA performance was impaired on both high and low executive attention demand conditions, with worse performance overall on the semantic compared to the perceptual version. While these results are consistent with the presence of a sustained attention deficit in conjunction with a semantic processing deficit, as previously discussed, they are also consistent with a stimulus-response (SR) mapping deficit, as these demands were equal between conditions within each experiment, but greater in the semantic compared to perceptual tasks given the nature of the classification and the number of stimuli.

In experiments three and four, PWA presented with task maintenance deficits in spatial Stroop, but impaired performance across congruency type in the hard executive attention condition in word picture interference. It was claimed that this pattern could also be due to SR mapping differences between tasks. Although speculative, these claims regarding SR mapping deficits in PWA are testable: for example, experimental paradigms used to test “rule working memory” based on stimulus-response mapping complexity (e.g., Duncan, 2012) should be sensitive the effects described in this section. The focus of discussion will now shift to the predictions of specific aim 2 and results from experiments 5 and 6.

Specific aim 2 predicted that PWA would present with deficits in adapting to speed and accuracy task constraints in both lexical decision and numerosity judgment. These effects were found in the behavioral data on response accuracy and response times, and on nondecision times ($t_0$) in the diffusion model, but were not found on boundary width ($a$), where they were initially predicted to occur. Instead, PWA responded to task constraints by shifting boundary widths similarly to controls, but also set much more conservative boundary widths across task and condition, with some evidence for disproportionately conservative boundaries in the neutral task condition for lexical decision. This can be interpreted as a maladaptive response to the experience of encountering processing difficulty following stroke, as boundary widths set beyond a certain width provide diminishing returns once the pass the point at which within-trial noise in the drift rate parameter begins to average out (Starns, May 2015, personal communication).

Although the group by task interaction found on nondecision times across experiments was not predicted, it does appear to be evidence for a task adaption deficit in PWA, as they were unable to reduce nondecision times in the manner MCs were in contexts of speed pressure. This effect was interpreted based on work by Rinkenauer et al. (2004), who argued that task adaption to speed pressure exerted separate measurable effects both before and after response selection. Executive attention task maintenance measures did not mediate these effects, suggesting dissociation of these control functions.

Analyses of drifts rates revealed that PWA had worse drift rates than MCs in the lexical decision task overall, and also had disproportionately poor performance in the easiest stimuli conditions in both the lexical decision and numerosity tasks, indicating less efficient processing in these contexts. The first of these findings confirms the lexical processing difficulties predicted for this population. The second of these findings was not predicted, and points to a more general information accumulation deficit. Again, executive attention task maintenance measures did not mediate these effects.

One possible explanation for the overall pattern of group performance across experiments 5 and 6 has already been introduced: a PWA deficit in SR mapping in conjunction with lexical processing impairments could account for both drift rate and nondecision time effects across these experiments. Support for this claim comes from a) the arguments of Rinkenauer et al. (2004), who claimed speed exerts pressure both before and after response execution, and b) work by Schmiedek et al. (2007), who claimed that relationships between EZ diffusion drift rates on hard and easy tasks and working memory measures could be explained by a SR mapping account of working memory, and not by an executive attention-based account, due to the fact that the easy tasks had little in the way of inhibition demands.

Putting these claims and findings together, SR mapping could be a common factor that allows for faster pre-response selection by acting on drift rates, and faster post-response selection by acting on nondecision times. This would account for group differences in nondecision times, as PWA with mapping deficits might be unable to efficiently activate preferred motor patterns based on response uncertainty. This could also account for the specific pattern of group interactions on drift rates in the following manner: if SR mapping affects the efficiency of evidence accumulation ($v$), it must only be a partial contributor; factors affecting the difficulty of the classification itself (e.g., word frequency in lexical decision) must also provide unique contributions to drift rate. In this view, a drift rate can be conceived as a composite measure, incorporating individual contributions from SR mapping demands and stimulus classification demands to determine an overall rate. PWA deficits in SR mapping ability should therefore affect drift rates in both lexical decision and numerosity tasks. In contrast, PWA deficits in lexical processing should only affect lexical decision drift rate. If both these effects are assumed to be purely additive and roughly equal in contribution, the SR mapping deficit would produce a group by stimuli type interaction in both tasks (i.e., poor SR mapping ability would have a disproportionate effect on the processing of the easiest stimuli types), whereas the lexical processing deficit would produce a main effect of group only on lexical decision. These were the effects found in experiments 5 and 6.

While this SR mapping deficit account integrates a number unexpected findings from the current set of experiments, it unfortunately obviates one of the major benefits generally gained by applying the diffusion model to behavioral response data: namely, the analytical clarity that comes from being able to map specific experiment manipulations and cognitive operations to specific model parameters. Unfortunately in this case, parsimony supports the suggestion that a single cognitive ability, SR mapping, affects both pre-and post decision processes, making a one-to-one mapping between specific operations and parameters less tenable in this context.

If the SR mapping account is correct, it also provides a rationale for the lack of relationship between task maintenance measures and group effects on drift rate and nondecision time, as the calculated difference scores were specifically designed to capture the task maintenance/proactive inhibition elements of the executive attention construct, and minimize any contributions from stimulus-response mapping on these tasks.

In conclusion, the current work found evidence for the predicted domain-general and domain-specific impairments in executive attention at the level of individual PWA. Executive attention deficits did not appear to be associated with difficulties adapting to shifting speed-accuracy constraints, at least as currently measured.

In addition, group-level patterns of performance across experiments suggest an additional related but distinct executive deficit in the area of generating and maintaining arbitrary stimulus-response mappings, which is worthy of targeted investigation in future work. This study also demonstrated the appropriateness and potential applicability of the diffusion model in aphasia research, although given the current conclusions, comes with the caveat that this modeling approach is most useful when careful experimental design ensures manipulations map differentially onto specific model parameters.

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